2018

Evaluation of Traffic Incident Timeline to Quantify the Performance of Incident Management Strategies

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EVALUATION OF TRAFFIC INCIDENT TIMELINE TO QUANTIFY THE PERFORMANCE OF INCIDENT MANAGEMENT STRATEGIES

By

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A thesis submitted to the School Engineering

In partial fulfillment of the requirements for the degree of

Masters of Science in Civil Engineering

UNIVERSITY OF NORTH FLORIDA

COLLEGE OF COMPUTING, ENGINEERING, AND CONSTRUCTION

April 2018

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DEDICATION

In dedication to my beloved parents Joseph and Eleonora.

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to the Almighty God, in whom I trust. I convey my immense thanks to my supervisor, Dr. Thobias Sando, whose expertise, understanding, and patience, added considerably to my accomplishments. Very special thanks to the members of the committee, Dr. Don Resio and Dr. Ching-Hua Chuan who reviewed and provided invaluable guidance in the preparation of this thesis.

This project was funded by the Florida Department of Transportation (FDOT) and conducted by the University of North Florida (UNF). Hence, my sincere gratitude is towards all personnel at the Regional Traffic Management Center (RTMC) in Jacksonville, Florida. The opinions, results, and findings of this thesis are those of the author and do not necessarily represent the opinion of the FDOT, UNF or the RTMC.

To members of the UNF transportation lab, thank you for being there for me, it was a great experience working with you.

Above all, I would like to thank my family and friends. To my father and siblings, thank you for your love and encouragement in my life. You are a blessing.

TABLE OF CONTENT

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS

AFT	Accelerated Failure Time
AIC	Akaike Information Criterion
CCTV	Closed Circuit Television
EMS	Emergency Medical Services
FDOT	Florida Department of Transportation
FHP	Florida Highway Patrol
FHWA	Federal Highway Administration
HSP	Highway Safety Patrol
HELP	Highway Emergency Local Patrol
I-10	Interstate 10
I-295	Interstate 295
I-75	Interstate 75
I-95	Interstate 95
IRT	Incident Response Team
ITS	Intelligent Transportation System
JSO	Jacksonville Sheriff's Office
LASSO	Least Absolute Shrinkage and Selection Operator
MAC	Media Access Control

MAPE	Mean Absolute Percentage Error
RTMC	Regional Traffic Management Center
SR-202	State Road 202
TMC	Traffic Management Center
TMS	Transportation Management Systems
VIF	Variance Inflation Factor
VMS	Variable Message Signs

ABSTRACT

Transportation agencies are introducing new strategies and techniques that will improve traffic incident management. Apart from other indicators, agencies measure the performance of the strategies by evaluating the incidents timeline. An effective strategy has to reduce the length of the incident timeline. An incident timeline comprises various stages in the incident management procedure, starting when the incident was detected, and ending when there is the recovery of normal traffic conditions. This thesis addresses three issues that are related to the traffic incident timeline and the incident management strategies.

First, co-location of responding agencies has not been investigated as other incident management measures. Co-location of incident responders affects the incident timeline, but there is a scarcity of literature on the magnitude of the effects. Evaluation of the co-location strategy is reflected by the response and verification durations because its effectiveness relies on improving communication between agencies. Investigation of the response and verification duration of incidents, before and after operations of a co-located Traffic Management Center (TMC) is done by using hazard-based models. Results indicate that the incident type, percentage of the lane closure, number of responders, incident severity, detection methods, and day-of-the-week influence the verification duration for both the before- and after- period. Similarly, incident type, lane closure, number of responders, incident severity, time-of-the-day, and detection method influence the response duration for both study periods. The before and after comparison shows significant improvements in the response duration due to co-location of incident response agencies.

Second, the incident clearance duration may not necessarily reflect how different types of incidents and various factors affect traffic conditions. The duration at which the incident influences traffic conditions could vary – shorter than the incident duration for some incidents and longer for

others. This study introduces a performance measure called ***incident impact duration*** and demonstrates a method that was used for estimating it. Also, this study investigated the effects of using incident impact duration compared to the traditionally incident clearance duration in incident modeling. Using hazard-based models, the study analyzed factors that affect the estimated incident impact duration and the incident clearance duration. Results indicate that incident detection methods, the number of responders, Traffic Management Center (TMC) operations, traffic conditions, towing and emergency services influence the duration of an incident.

Third, elements of the incident timeline before the clearance duration have been overlooked as factors that influence the clearance duration. Incident elements before the clearance duration include verification time, dispatch duration, and the travel time of responders to the incident scene. This study investigated the influence of incident timeline elements before clearance on the extent of the clearance duration. Also, this study analyzed the impact of other spatial and temporal attributes on the clearance duration. The analysis used a Cox regression model that is estimated using the Least Absolute Shrinkage and Selection Operator (LASSO) penalization method. LASSO enables variable selection from incidents data with a high number of covariates by automatically and simultaneously selecting variables and estimating the coefficients. Results suggest that verification duration, response travel duration, the percentage of lane closure, incident type, the severity of an incident, detection method, and crash location influence the clearance duration.

Keywords: Traffic management center; Traffic incident timeline; Verification duration; Response duration; Incident clearance duration; Hazard based models

CHAPTER 1 INTRODUCTION

Background

Traffic incidents pose a continuous challenge to incident management agencies. As long as there is traffic on roadways, there is a possibility for the occurrence of an incident. Traffic incidents are described as non-recurrent events that reduce the roadway capacity and/or increase in demand (Amer et al., 2015). Traffic incidents can occur in the form of a traffic crash, vehicle breakdown, or roadway hazards. Unfortunately, no incident is an end in itself, a crash can lead to a secondary crash, a vehicle breakdown can cause delays, and a hazard can cause a crash. To limit the consequences of traffic incidents, transportation agencies are implementing various incident management strategies.

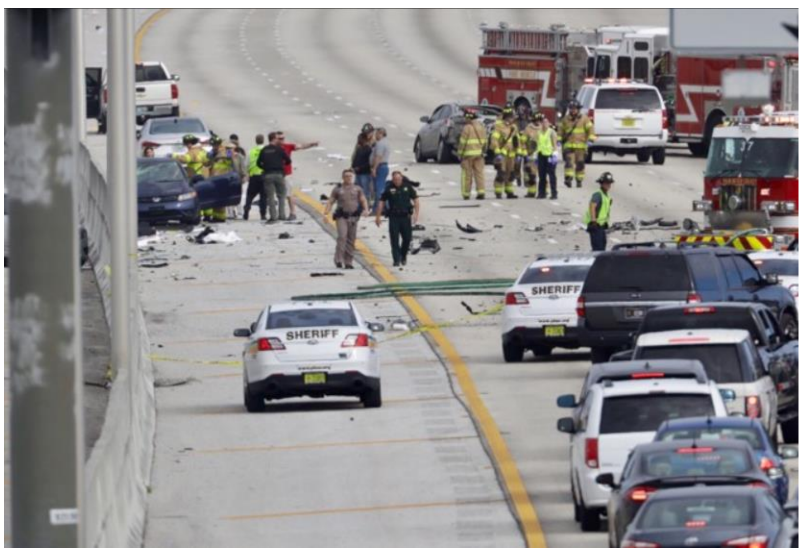


Figure 1.1 Traffic crash scene (Palm Beach Post, 2018)

The main function of incident management strategies is to respond and clear traffic incidents quickly and safely. Strategies that are frequently used include on-road help programs (e.g. Road Rangers) and several forms of Intelligent Transportation Systems (ITS), e.g. variable message signs (VMS). In order to have full control on the implemented strategies, transportation agencies use Regional Traffic Management Centers (RTMCs) whose function is to monitor traffic conditions and manage traffic management resources in a specific region (Owens et al., 2010).

Traffic management centers (TMCs) are multimillion-dollar projects. Recently, a new Regional Traffic Management Center (RTMC) started operating in Jacksonville, Florida and was constructed at the cost of about 11 million dollars. The new RTMC manages traffic incidents on interstates and arterial roadways in North Florida and Gainesville. The new facility has FDOT staff, RTMC operators and Florida Highway Patrol (FHP) personnel located in the same building. Although not all incident management stakeholders are in the facility yet, the presence of all responders in one building is expected to improve traffic incident management.

Amongst other measures, the incident timeline is used to assess the performance of incident management strategies (Conklin et al., 2013). The incident timeline, as shown in Figure 1.2, starts when an incident occurs, key interim milestones are identified, and ends with traffic returning to normal. For each incident, the key interim milestones are when the responders are contacted, responders arrive on the scene, lanes are closed, incident is cleared, and lanes are opened.

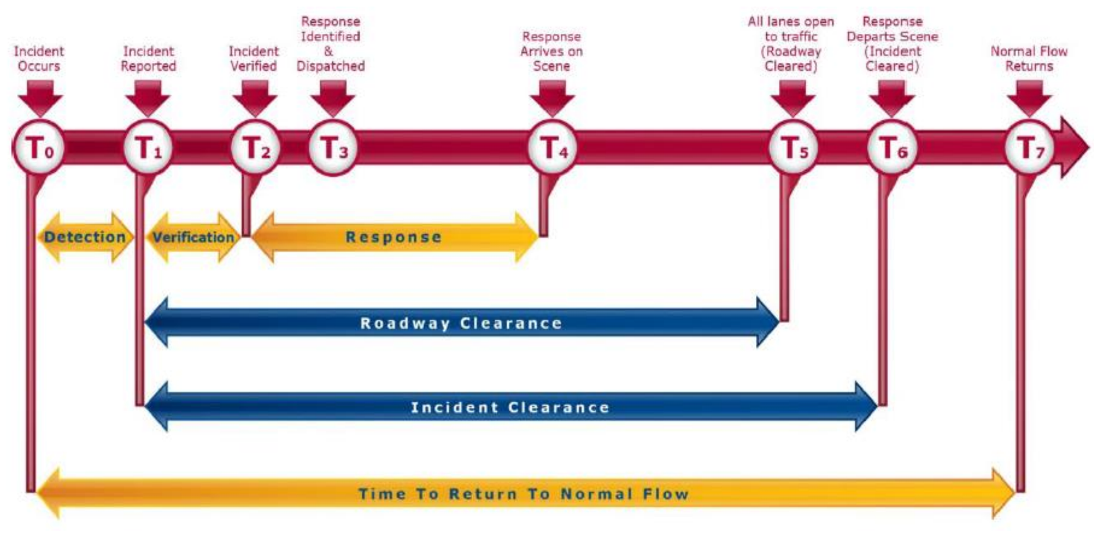


Figure 1.2 Traffic incident timeline (Amer et al., 2015)

Study objectives

The main objective of the study is to assess and quantify the performance of incident management strategies. Specifically, this study analyzes the effects of the co-location of incident management agencies in a facility. The elements of a traffic incident timeline are used to measure the performance of incident management strategies. The analysis applies duration models to accomplish the objective of the study.

Thesis Organization

This thesis contains five chapters. Chapter 1 provides the general overview of the research problem and the description of the research objectives. The next three chapters (Chapter 2, Chapter 3, and Chapter 4) are comprised of three research articles that are focused on the main objective of the study. Moreover, Chapter 5 gives the summary, conclusions, and recommendations for future studies based on the limitations of this study.

CHAPTER 2 : PAPER 1

Impact of co-location of response agencies on the traffic incident timeline

Paper 1 was submitted on 20th March, 2018 and is under review for publication in the Journal of Advances in Transportation Studies (ATS).

Introduction

Traffic incidents are a major cause of roadway congestions and hazardous safety conditions to road users. It is estimated that a quarter of the traffic congestion in the U.S. (Owens et al., 2010) and more than a half of the congestion on the nation's freeways is caused by traffic incidents (USDOT-ITS, 2000). As a result of un-cleared traffic incidents, responders and other travelers are exposed to the risk of secondary crashes (PB Farradyne, 2006), which can have significant impacts such as loss of life, injuries and damage of properties. Consequences of incidents intensify when it takes longer to clear them. For instance, about 4 minutes of travel time is lost for every minute of blocking a freeway lane during peak periods and the likelihood of a secondary crash occurrence increases by 2.8% for every minute that a primary incident remains active (Owens et al., 2010).

Incident management agencies are trying to reduce incident duration by introducing new strategies and improve the existing techniques to reduce the consequences of incidents that are not cleared. Various strategies have been applied, with the options ranging from policies such as the open road policy in case of Florida, the use of technologies such as WAZE, to the on-road help services such as Road Rangers. Savings of the incident-related 143.3 million travel hours and 3.06 million USD were observed in 2007 as result of improved incident management procedures nationwide (Owens et al., 2010). Introduction of specific programs such as Incidents Response Team (IRT) led to monetary savings of $20,600 to $61,800 per incident for just one county in the state of Washington (Carson, Mannering, Legg, Nee, & Nam, 1999). Despite the benefits, a strategy such as co-location of responding agencies has not been investigated. With representatives from transportation agencies, law enforcement, and other emergency service agencies sharing space and interoperable systems, co-location has potential of improving incident response (Owens et al., 2010).

Although it is expected that the incident timeline will be affected by the co-location of incident responders, the characteristics of its impact are not clear. The incident timeline is comprised of different duration elements that have varying impact on the existing incident and the roadway conditions. A typical incident timeline has the detection, verification, response, open roads (roadway clearance) and recovery duration (Amer et al., 2015). Improvements that are made on one element do not guarantee advances on the total incident duration. For example, one study found that an increase in the detection/reporting time of incidents was accompanied by a significant reduction in the response and clearance time of incidents (Nam & Mannering, 2000). Therefore, a specific investigation of each incident timeline element is important as it can decrease negative effects of the element on traffic operations (Lee & Fazio, 2005). Some incident duration elements are critical to the whole incident management process even though they are not long e.g., verification duration. Verification duration is important in determining accurate and detailed information which enables the dispatch of the most appropriate personnel and resources to the scene (USDOT-ITS, 2000). Previous studies have not focused on analyzing this part of the incident timeline even though it can influence clearance and total incident duration.

This study is aimed at evaluating factors that influence the verification and response duration of an incident. Apart from the incident timeline elements, the study focuses on evaluating the impact of co-locating response agencies under one roof i.e., in the Traffic Management Center (TMC) facility. Since co-location effectiveness relies on improving communication between agencies by providing the necessary details for optimum response which depends on accurate and rapid verification (USDOT-ITS, 2000), the study aims at evaluating effectiveness of co-location of response agencies using response and verification duration.

Literature Review

Incident timeline

There are inconsistencies in the way studies describe the incident timeline. Many have described the elements of the incident timeline as detection/reporting time, response time and clearance time (Carson et al., 1999; Chung, 2010; Ghosh & Savolainen, 2012; Kaabi, Dissanayake, & Bird, 2012; Lee & Fazio, 2005; Nam & Mannering, 2000). Conversely, some studies have added verification time (Amer et al., 2015; Pearce & Subramaniam, 1998) and recovery time or queue dissipation (Kaabi et al., 2012) in the incident timeline. Detection time and recovery time are incident timeline elements that are difficult to measure. For example, it is not feasible for incident management agencies to record the exact time when the incident occurred and the estimation of recovery time requires statistical methods in understanding traffic operations of the roadway when there is no incident. Although some studies have reported analyzing detection time (Kaabi, 2013; Nam & Mannering, 2000), there are limitations in deducing the exact time when an incident occurred (Nam & Mannering, 2000). On the other hand, estimation of recovery time is unpredictable due to its dependency on traffic conditions. Most incident management studies use incident timeline elements that can be directly measured such as reporting time, response time and clearance duration (Junhua, Haozhe, & Shi, 2013; Kaabi, 2013; Kaabi et al., 2012; Lee & Fazio, 2005; Nam & Mannering, 2000).

Verification and response duration

Incident verification is the determination of the precise location and nature of the incident (USDOT-ITS, 2000). It is the time between an incident being reported and the incident being verified (Amer et al., 2015). Verification helps prevent deploying resources to false incident reports (USDOT-ITS, 2000). With the varying definitions of the incident timeline, studies have included verification duration in the detection or reporting time (Chung, 2010; Kaabi, 2013). Others have included it in response duration by defining response as the time from incident notification to responder arrival at the scene (Junhua et al., 2013; Nam & Mannering, 2000). For this reason, results that were obtained from these studies somewhat apply to the verification duration. For example, a study by Carson et al. (1999) found that detection and reporting (included verification duration) were longer for incidents that occurred in the rain and which involved an injury or fatality but they were shorter for incidents that occurred during the morning peak.

On the other hand, response duration is measured from the time incident response team was notified of an incident to when they arrived at the incident scene (Nam & Mannering, 2000). Response time include dispatch duration and travel time to the incident scene (Nam & Mannering, 2000). The incident response involves confirming incident occurrence, determination of exact location and obtaining as many relevant details as possible (Lee & Fazio, 2005). The incident response time is longer when the incident occurs in the afternoon peak and weekends but shorter if it involves hazardous material or debris (Carson et al., 1999). Incidents that occurred under daylight condition were associated with 12% faster response time compared to incidents during the night because most incidents occurred during daytime than nighttime (Kaabi, 2013). About 11% of expected response time are longer during weekdays than weekends and the expected response times on urban freeways are 23% shorter in urban freeways than in rural freeways during AM periods (Lee & Fazio, 2005). Unfortunately, studies that have analyzed the response duration defined it differently such that the analysis provides varying inference on the incident management procedures (Kaabi, 2013; Lee & Fazio, 2005; Nam & Mannering, 2000). The optimum response is sending the right equipment to the incident scene quickly without under- or over-responding which can increase cost and degrade the effectiveness of the response (USDOT-ITS, 2000). In many areas of the U.S. incident response components from different agencies continue to be dispatched independently and the priorities vary by agency e.g, minimizing delays or scene security (USDOT-ITS, 2000).

Co-location of response agencies

Interagency coordination can improve detection and response times (USDOT-ITS, 2000). For example, in Florida one of the Transportation Management Systems (TMS) strategies is to encourage co-location of FDOT-TMC and law enforcement dispatch centers (PB Farradyne, 2006). Considering that incident response can be controlled by incident management teams (Lee & Fazio, 2005), co-location of incident response agencies is expected to improve incident management procedures. None of the previous studies investigated the effect of co-location of response agencies. Moreover, there is scarcity in the number of studies investigating verification and response duration as performance measures for the incident management procedures. It is thus the aim of this study to analyze incident verification and response durations, and evaluate the impacts of co-location of incident management agencies on the incident timeline.

Methodology

Data description

The incident data were obtained from SUNGUIDE database, a repository of incident information for the FDOT. The study used incident data from 2014 to 2017 for interstate system in the cities of Jacksonville and Gainesville, Florida. The database recorded incidents that occurred on Interstate 10 (I-10), Interstate 95 (I-95), Interstate 295 (I-295), Interstate 75 (I-75), and State Road 202 (SR-202). During that period, the database recorded 98,754 incidents, which included crashes, hazards such as roadway debris, and vehicle problems such as disabled and abandoned vehicles. Incident data contained critical information on the incident timeline including verification duration, response duration and other spatiotemporal attributes related to incidents. In an attempt to study the effect of co-location of response agencies, data were divided into two groups; before co-location (2014-2015) and after co-location (2016-2017). Data for the before period contained 55,668 incidents while the after period contained 43,086 incidents. Operations of the co-located facility started in mid November 2015 but the data for November and December were analyzed in the before period because the new strategy was not effective in the beginning month of operations.

Model formulation

To study duration data, hazard-based models were employed to describe the conditional likelihood of an incident ending at some time *T* given that the duration has continued until time *t*. The hazard-based models consider *T* as a random variable time and *t* as a specific time. The cumulative density function and the density function are represented in Equations 2.1 and 2.2, respectively. In Equation 2.1, *P* represents the probability of the incident to survive at time *t*. The hazard function is described by Equation 2.3 that shows the conditional probability for an event to occur at time *T* given that it has not occurred until time *t* (Washington, Karlaftis, & Mannering, 2003).

$$F(t) = P(T < t) \quad (2.1)$$

$$f(t) = \frac{dF(t)}{dt} \quad (2.2)$$

$$h(t) = \frac{f(t)}{[1-F(t)]} \quad (2.3)$$

Moreover, the first derivative of the hazard function with respect to time shows the probability of the duration ending soon after it has lasted for as long as it has. If $(dh(t))/dt > 0$ for all values of t, then the hazard is monotonically increasing, which means the probability that the incident will end soon increases as the incident duration lasts longer. If $(dh(t))/dt < 0$ for all values of t, then the hazard is monotonically decreasing, which means the probability that the incident will end soon decreases as the incident duration lasts longer. When $(dh(t))/dt < 0$ for some values of t and $(dh(t))/dt > 0$ for other values of t, then hazard is non-monotonically decreasing, which means the probability that the incident will end soon decreases or increases depending on how long it has lasted. But if $(dh(t))/dt = 0$ for all values of t, then the probability that the incident will end soon does not depend on how long it has lasted (Nam & Mannering, 2000; Washington et al., 2003).

For the hazard-based models to take account of the covariates, the accelerated failure time model is used. This hazard model type assumes that covariates rescale time directly in the survivor function. The accelerated failure model hazard function is written as Equation 2.4. The $ho(t)$ denotes the baseline hazard function, X is a covariate vector, and β is a vector of estimable parameters (Washington et al., 2003). For the applied accelerated failure time model, there is a need to assume a particular shape for the hazard rate. In this study, three shapes, Weibull, log-logistic and lognormal distributions, were examined.

$$h(t|X) = h_o[tEXP(\beta X)]EXP(\beta X) \tag{2.4}$$

The Weibull distribution allows for monotonic increasing, monotonic decreasing and independent hazard. The hazard is monotone increasing in duration if the Weibull distribution parameter $p > 1$, and if $p < 1$, the hazard is monotone decreasing in duration while if $p = 1$, the hazard is constant in duration. The log-logistic allows for non-monotonic hazard functions such that for a log-logistic distribution with $p < 1$ then the hazard is monotone decreasing in duration. If $p > 1$ then the hazard increases in duration from zero to an inflection point and decreases towards zero after that but if $p = 1$ then the hazard is monotone decreasing in duration from parameter λ of the log-logistic distribution (Washington et al., 2003).

Determination of changes in the durations after incident response agencies were co-located under the same roof is achieved by comparing the model coefficients in the respective study periods (before- and after- co-location). A *z*-test shown in Equation 2.5 can be used to determine if the difference between coefficients of the two models (one for the before- and another for the after- period) are statistically significant (Paternoster, Brame, Mazerolle, & Piquero, 1998; Spohn & Homey, 1993). In Equation 2.5, β1 is the model coefficient in the before period, β2 is the model coefficient in the after period; SEβ1 and SEβ2 are the standard errors of the corresponding coefficients. The plausibility of the selected test is checked considering all of the required conditions as suggested by Brame et al. (1998), for example the presence of two mutually exclusive populations with comparable measurements on a dependent variable and a vector of corresponding independent variables.

$$z = \frac{\beta_1 - \beta_2}{\sqrt{SE\beta_1^2 - SE\beta_2^2}} \tag{2.5}$$

Model variables

Four models were developed – two for each duration (response and verification) for both before (2014-2015) and after (2016-2017) period. The independent variables; lane closure and a number of responders were continuous while all other variables were categorical. The variable for incident type included vehicle problems, which was a collective name for all incidents involving vehicle issues apart from crashes, such as disabled vehicles, abandoned vehicles, and vehicle fire.

Hazards included roadway debris, spills, and flooding. In the detection method variable, a category for road users included all methods which a road user is a primary source on the occurrence of an incident e.g. motorist calls and WAZE. A detection method category named other methods represented sources such as construction offices and maintenance asset managers. Table 2.1 shows the summary of all independent variables used in the model.

Table 2.1 Summary of independent variables for the duration models

		Verification duration				**Response duration**			
		2014-2015		**2016-2017**		**2014-2015**		**2016-2017**	
Variable	**Categories**	**Count**	**Mean**	**Count**	**Mean**	**Count**	**Mean**	**Count**	**Mean**
Incident attributes									
Incident type	Hazards	1623	18	2752	15	389	19	258	20
	Crashes	10323	23	10391	20	3427	16	3989	14
	Vehicle problems	3506	17	980	16	3370	14	2742	13
Lane closure	Continuous	15452	21	14123	19	7186	15	6989	14
Ramp involvement	Absent	14870	21	13582	19	6681	16	6579	14
	Present	582	13	541	10	505	11	410	8
Severity	Minor	14201	21	12616	20	5991	16	5712	15
	Moderate	892	13	987	10	859	11	918	10
	Severe	359	14	520	11	336	10	359	9
Spatiotemporal attributes									
Roadway	I-10	2643	21	2066	21	916	19	689	15
	I-95	4296	20	4429	18	3009	14	2573	14
	I-295	5402	20	5224	17	2760	15	3223	14
	SR 202	1196	22	839	19	325	15	330	16
	I-75	1915	23	1565	23	176	22	174	18
Time of day	Peak hour	7830	19	7084	18	4457	14	4086	13
	Off peak	7622	22	7039	19	2729	18	2903	15
Season of the year	Spring	4928	21	6210	17	2316	15	3278	13
	Summer/Fall	10524	20	7913	20	4870	15	3711	15
Day of the week	Weekend	2886	24	2564	22	679	22	727	19
	Weekday	12566	20	11559	18	6507	15	6262	13
Agency operations									
Number of responders	Continuous	15452	21	14123	19	7186	15	6989	14
Detection method	JSO	269	14	117	13	174	11	64	10
	Road users	281	17	810	13	181	17	416	14
	CCTV/ TMC Operations	152	14	50	12	2959	13	1906	13
	D2 Road Rangers					45	10	48	7
	Florida Highway Patrol (FHP)	14709	21	13133	19	3784	17	4512	15
	Other methods	41	17	13	16	43	13	43	15

Results and Discussions

Descriptive statistics

Out of 55,668 incidents in 2014-2015, 15,452 incidents contained verification duration information that can be analyzed while 14,123 incidents out of 43,086 were analyzed in 2016-2017. Because some incidents had incomplete data and others were coded as having a zero response duration, only 7186 and 6989 incidents were analyzed in the 2014-2015 and 2016-2017, respectively. Summary statistics shown in Table 2.1 suggest that for most of the incident categories, the mean durations (both verification and response) decreased from 2014-2015 to 2015-2016. For example, the mean verification duration for crashes was 23 minutes in the before period as compared to 20 minutes in the after period. Similarly, the response duration for incidents that were detected by the Florida Highway Patrol (FHP) decreased from 17 minutes to 15 minutes.

Figure 2.1(a) shows the distribution of incidents verified in 1 minute and above within the two study periods. The percentage of crashes in 2016-2017 is higher than that in 2014-2015. Figure 2.1(b) shows the distribution of incident types responded in both periods whereby the percentage of crashes increased by 9%. The observable increase in crashes can be attributed to the nationwide trend regarding the increasing rate of crashes in the recent years. Conversely, Figure 2.1(a & b) shows a decrease in the percentage of verified and responded hazards and vehicle problems. This observation may be due to the improved on-road help services which have ensured that most of the hazards and vehicle problems are dealt with as soon as detected.

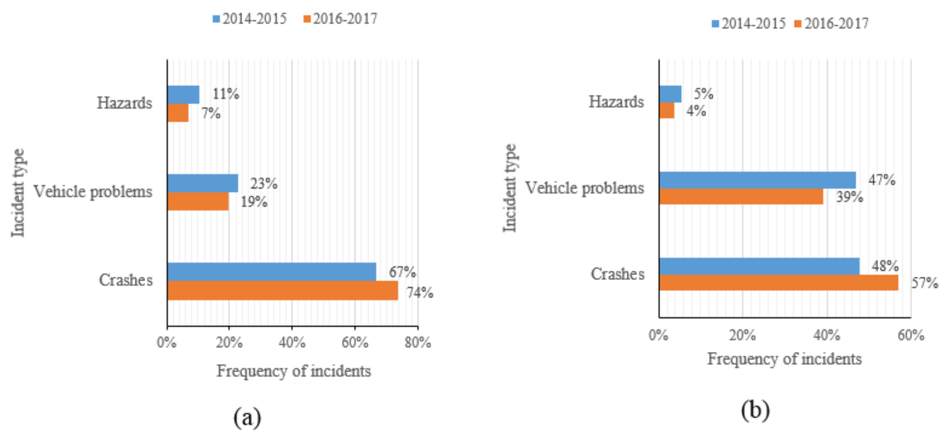


Figure 2.1 Distribution of (a) verification and (b) response duration according to the incident type

Modeling results

According to the Akaike information criterion (AIC) value, the log-logistic distribution provides the best fit for both; incident verification and response duration data (Table 2.2 and Table 2.3) as compared to Weibull and lognormal distributions. For the model results in Tables 2.2 and 2.3, the third column shows the fitted model coefficients based on Equation 2.4. This study adopted a 95% confidence level to test the significance of the effects of model variables on incident duration. Therefore, a p-value of 0.05 is a threshold for the significance level. A column that depicts the percentage (%) change shows the difference in the percentage of the incident duration of a corresponding factor-level compared to the base factor-level. For example, for incident type factor, the hazard is a base level. A six percent (6%) change shown in Table 2.2 for 2014-2015 data on crashes factor is the difference in incident verification duration between crashes and hazards.

Table 2.2 Modeling results for verification duration before and after co-location of agencies

Variable	Categories	2014-2015 Estimates	2014-2015 *p*-value	2014-2015 % Change	2016-2017 Estimates	2016-2017 *p*-value	2016-2017 % Change	Z-test
Incident attributes								
Incident type	Hazards							
	Crashes	0.059	0.019	6	0.065	0.038	7	-0.172
	Vehicle problems	-0.155	0.000	-14	-0.133	0.000	-12	-0.474
Lane closure	Continuous	-0.881	0.000	-59	-1.080	0.000	-66	1.760
Ramp involvement	Absent							
	Present	-0.105	0.180	-10	0.054	0.715	6	-0.951
Severity	Minor							
	Moderate	0.093	0.039	10	0.085	0.046	9	0.140
	Severe	0.409	0.000	50	0.438	0.000	55	-0.255
Spatiotemporal attributes								
Roadway	I-10							
	I-95	-0.052	0.019	-5	-0.161	0.000	-15	3.207
	I-295	0.016	0.451	2	-0.198	0.000	-18	6.474
	SR 202	0.110	0.000	12	-0.013	0.727	-1	2.521
	I-75	-0.073	0.006	-7	-0.063	0.045	-6	-0.241
Time of day	Peak hour							
	Off peak	0.070	0.000	7	-0.003	0.846	0	3.303
Season of the year	Spring							
	Summer/Fall	0.014	0.352	1	0.117	0.000	12	-4.586
Day of the week	Weekend							
	Weekday	0.073	0.000	8	-0.070	0.001	-7	4.871
Agency operations								
Number of responders	Continuous	-0.286	0.000	-25	-0.257	0.000	-23	-2.380
Detection method	JSO							
	Road users	-0.222	0.003	-20	-0.382	0.000	-32	1.311
	CCTV/ TMC Operations	-0.315	0.001	-27	-0.506	0.002	-40	0.999
	FHP	0.119	0.030	13	0.025	0.781	2	0.906
	Other methods	-0.063	0.686	-6	-0.049	0.857	-5	-0.044
Constant		3.061	0.000		3.204	0.000		
Log(p)		-0.703	0.000		-0.621	0.000		
p		2.020			1.858			
AIC		114374			103980			

Verification duration

Results for the verification models presented in Table 2.2 suggest that; incident type, the percentage of lane closure, number of responders, incident severity, roadway, detection method and day-of-the-week are significant factors before- and after- co-location of responders. Roadway (SR-202) and season of the year are significant factors for the verification duration after co-location only while FHP and time-of-the-day are significant factors for the before co-location. The distribution parameter (*p*) for both the before (2.020) and after (1.858) periods are more than one (p>1) suggesting that the hazard functions for verification duration are non-monotonic (lower part of Table 2.2). The hazard increases from zero to a maximum at an inflection point and decreases to zero after that. The evolution of the inflection point between the two periods as suggested by unequal distribution parameters show changes in the verification duration due to the co-location of responding agencies.

Incident attributes

The data shown in Table 2.2 indicate that crashes have verification durations that are longer than hazards for both before and after co-location of response agencies. Verification of crashes is usually done using CCTV cameras as opposed to on-road help services that detect and verify hazards. Detection of a crash using CCTV cameras requires extra effort and time when confirming the location and attributes of the crash. The difference of verification duration between crashes and hazards is 6% and 7% for the before- and after- period, respectively. Table 2.2 shows that the difference between verification duration of crashes before and after co-location of responding agencies is not significant at 95% level of confidence. Verification duration of vehicle problems is 14% (for the before- period) and 12% (for the after-period) quicker than hazards due to the effectiveness of on-road help services (Road Rangers) in detecting and verifying vehicle problems. Similar to the verification of crashes, the difference between verification of vehicle problems before and after co-location is not significant at 95% level of confidence.

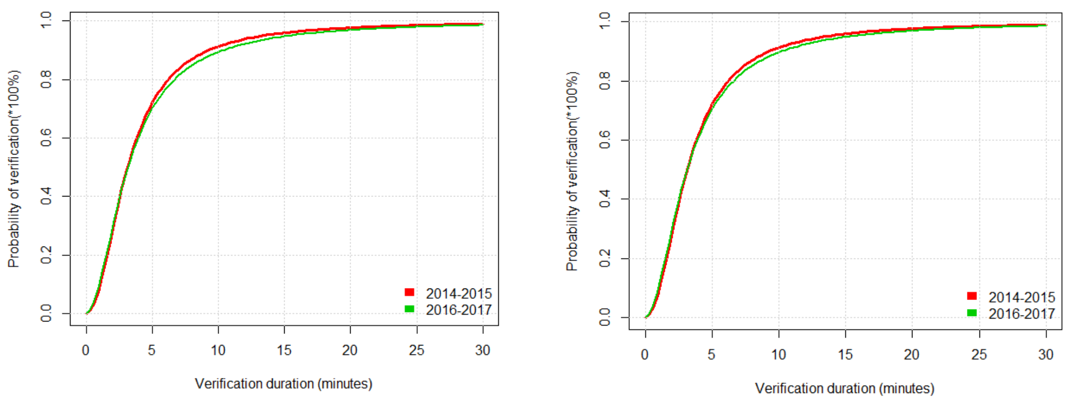
Based on the results displayed in Table 2.2, the increase in the percentage of lane closure leads to a decrease in the verification duration for both periods. A 59% and 66% decrease in the verification duration is associated with a unit change in the percentage of lane closure for before- and after co-location, respectively. A higher percentage of lane closure can cause bottlenecks due to the reduced capacity, leading to easy detection by the TMC personnel through CCTV. Also, TMC staff can get a clue about the presence of these severe incidents from the roadway congestion maps. The effectiveness of CCTV and roadway congestions maps are improved by having responding agencies under one roof sharing similar video feed of incidents and communicate directly when making decisions. Severe incidents have 50% and 55% longer verification durations than minor incidents. Selection of the appropriate response for the severe incidents influences the length of the verification duration. However, results in Table 2.2 does not suggest a significant change in the verification duration of severe incidents between before and after co-location of incident responders.

Spatiotemporal attributes

Incidents that occur on I-95 and I-75 have shorter verification durations compared to incidents that occur on I-10 for both before- and after- periods. Table 2.2 shows a small percentage change in verification duration between incidents on I-75 and I-95 as compared to I-10. Also, the difference in verification duration due to co-location of response agencies is significant for I-95, I-295 and SR-202. For example, verification duration of incidents on I-95 are quicker after co-location of response agencies than before co-location. Further investigation on roadway characteristics has to be performed to identify the existing difference between the studied roadways.

Incidents that occurred during off-peak hours had longer verification durations compared to incidents during the peak hours in the period before co-location of responding agencies. Due to the expectation of incidents during the peak hours, TMC operators handle incidents that occur during peak hours quicker compared to incidents that occur during off-peak hours. Also, off-peak hours incidents include those during the nighttime when the response agencies are short staffed. Conversely, Table 2.2 show that the verification of incidents during off-peak hours is slightly quicker than during peak hours after the co-location of response agencies. The difference of verification duration between off-peak hours and peak hours for the after period is almost 0% as compared to 7% in the before period. The z-statistic in Table 2.2 suggest that the difference between verification duration of incidents during off-peak hours for before and after co-location of responders is significant at 95% level of confidence. A graphical representation of the results (Figure 2.2a) shows that the likelihood of verifying incidents during off-peak hours in more than 5 minutes is higher in the period before co-location as compared to after co-location of the response agencies. For example, in the Figure 2.2a, the probability of verifying incidents in less than 10 minutes is 90% in the before period and 88% in the after period. Also, Figure 2.2a shows that the likelihood of verifying incidents in less than 5 minutes is similar before and after co-location of responders.

Moreover, for the before- period, incidents that occur on weekdays have longer verification durations compared to incidents that occur on weekends. Verification duration during weekdays is shorter than weekends for the after- period. Figure 2.2b shows that the probability of verifying incidents in more than 5 minutes on weekends is higher in the before period than after co-location of responders. For example, in the Figure 2.2b, the probability of verifying incidents in less than 10 minutes is 90% in the before period and 89% in the after period. Likelihood of verifying incidents after co-location of responding agencies in less than 5 minutes is similar to that before co-location (Figure 2.2b). The difference of verification duration on weekends between before and after co-location is statistically significant at 95% level of confidence.



(a)

(b)

Figure 2.2 Probability of verification of incidents (a) during off-peak hours and (b) on weekends

Agency operations

Table 2.2 suggests that an increased number of responders is associated with the decrease in the verification duration. For a unit increase in the number of responders there is a 25% and 23% decrease in the verification duration for the before- and after- period, respectively. Incidents with many responders are ones that were quickly to be verified. This may imply that quick verification is associated with dispatch of incident responders without evaluation of the optimum response required for a particular incident.

Incidents that were detected by CCTV/TMC operations, road users (motorists and WAZE) have shorter verification durations than incidents detected by Jacksonville Sheriff's Office (JSO) for both study periods. Incidents detected by CCTV are verified quicker because incident responders can visually confirm by using video screens at the TMC. It is yet to be known what might be factors causing a significant difference in verification duration of incidents detected by the road users as compared to JSO. Based on the results shown in Table 2.2, incidents that are detected by the FHP have longer verification duration as compared to incidents that are detected by JSO in both periods. This observation may be influenced by presence of fewer incidents that were detected by JSO than FHP in the analysis.

Table 2.3 Modeling results for response duration before and after co-location of agencies

		2014-2015			**2016-2017**			
Variable	**Categories**	**Estimates**	***p*-value**	**% Change**	**Estimates**	***p*-value**	**% Change**	**Z-test**
Incident attributes								
Incident type	Hazards							
	Crashes	-0.269	0.000	-24	-0.267	0.000	-23	-0.429
	Vehicle problems	-0.197	0.002	-18	-0.314	0.000	-27	1.009
Lane closure	Continuous	-0.476	0.000	-38	-0.594	0.000	-45	0.623
Ramp involvement	Absent							
	Present	-0.001	0.991	0	-0.045	0.776	-4	0.363
Severity	Minor							
	Moderate	0.232	0.000	26	0.314	0.000	37	-0.911
	Severe	0.188	0.063	21	0.307	0.001	36	-1.142
Spatiotemporal attributes								
Roadway	I-10							
	I-95	0.003	0.944	0	0.042	0.373	4	-0.722
	I-295	-0.066	0.133	-6	0.100	0.031	11	-2.868
	SR 202	-0.081	0.265	-8	-0.036	0.629	-3	-0.584
	I-75	-0.340	0.000	-29	-0.408	0.000	-34	0.694
Time of day	Peak hour							
	Off peak	-0.065	0.022	-6	-0.143	0.000	-13	2.120
Season of the year	Spring							
	Summer/Fall	0.005	0.866	0	0.055	0.035	6	-1.493
Day of the week	Weekend							
	Weekday	-0.137	0.005	-13	-0.047	0.298	-5	-1.057
Agency operations								
Number of responders	Continuous	-0.252	0.000	-22	-0.253	0.000	-22	0.174
Detection method	JSO							
	Road users	0.193	0.112	21	0.498	0.001	65	-1.504
	CCTV/ TMC Operations	0.087	0.345	9	0.221	0.133	25	-0.761
	D2 Road Rangers	-0.791	0.000	-55	-0.434	0.043	-35	-1.703
	FHP	0.189	0.039	21	0.352	0.016	42	-0.939
	Other methods	0.006	0.974	1	0.532	0.019	70	-1.772
Constant		2.913	0.000		2.668	0.000		
Log(p)		0.075	0.000		0.054	0.000		
p		0.926			0.952			
AIC		46561			46412			

Response duration

Results in Table 2.3 show that incident type, percentage of lane closure, number of responders, moderate severity, time of the day, roadway (I-75), and detection methods (Road Rangers and FHP) are variables that are significant for the response duration in both study periods. Moreover, the presence of a ramp and day-of-the-week are significant variables in the before-period only, while severe incident, roadway (I-295), the season of the year and road users are significant factors in the after- period only. The distribution parameter (p) for both the before (0.926) and after (0.952) periods are less than one (p<1) which suggest that the hazard functions for response duration are monotonically decreasing in duration.

Incident attributes

Data in Table 2.3 show that crashes have 24% and 23% shorter response durations than hazards for the before- and after- period, respectively. Vehicle problems have 18% and 27% quicker response durations than hazards for the before- and after-period, respectively. The response for crashes is quicker compared to hazards because of the consequences related to crashes such as loss of life, which requires quicker response in order to save lives and reduce impacts on traffic operations such as secondary crashes. The results suggest that a percentage increase in the lane blockage is associated with 38% and 45% decrease in the response duration for the before- and after-period, respectively (Table 2.3). A high percentage of lane closure invoke attention from the incident managers into responding to an incident. Also, quick response for incidents with a high percentage of lane closure is critical because many incidents causing high percentage of lane closure are severe e.g. crashes. Moderate severity incidents have longer incident response durations when compared to minor incidents. Such a result may be attributed to the fact that more incidents in the analysis were in the minor category than moderate category.

Spatiotemporal attributes

Table 3 show that incidents that occur on I-75 have quicker response compared to incidents on I-10. Although I-75 significantly affect the response duration in both periods the difference between response duration before co-location and after co-location is not significant. The response duration before co-location for incidents on I-95 is significantly different from that after co-location at 95% level of confidence. For example, Figure 2.3a shows the probability of responding to incidents on I-95 in less than 50 minutes was 80% before co-location and is 85% after co-location.

Incidents that occur during off-peak hours have 6% and 13% shorter response duration compared to incidents that occur during peak hours for the before- and after- periods respectively (Table 2.3). Quicker response during off-peak hours is due to the traffic conditions, which shorten the travel time of the responders to the incident scene. Also, off-peak traffic conditions make the dispatch process easier by enabling responders to select the required resources for clearing incidents quickly. Figure 2.3b shows that the probability of responding to incidents during off-peak hours is higher in the after co-location period than before co-location. For example the probability of responding to incidents during off-peak hours in less than 50 minutes before co-location is about 82% and 90% after co-location. The z- statistic result suggest that the difference in response duration during peak hours between before co-location and after co-location is significant at 95% level of confidence. Co-location reduces the time agencies spend in selecting and dispatching the responders and ensures optimum response is selected such that travel time to the incident scene is reduced.

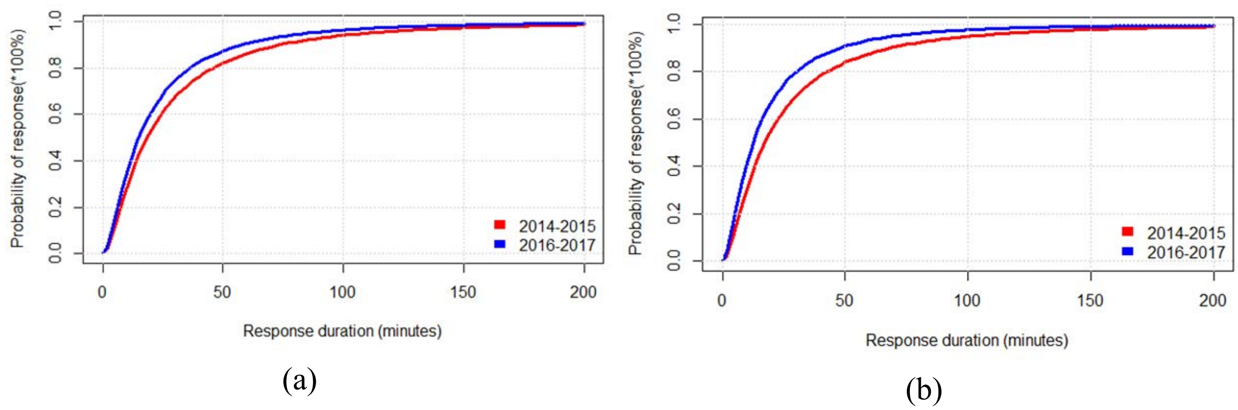


Figure 2.3 Probability of responding to (a) incidents occurring on I-95 and (b) incidents that occurred during off-peak hours

Agency operations

The results (Table 2.3) show that incidents with a high number of responders are associated with quicker response compared to incidents with a lower number of responders. Similar to the percentage of lane closures, a high number of responders is associated with incidents that are severe and require an immediate attention in order to save lives.

Incidents that were detected by Road Rangers have quicker response duration than incidents that detected by JSO. Effective communication between the Road Rangers to the TMC influence response duration for the incidents detected by the Road Rangers. Also, Road Rangers are quick to respond to hazards and vehicle problems which are a large fraction of incidents on freeways. Conversely, incidents detected by the FHP have longer response duration as compared to JSO. This is observation require further investigation but it may attributed by fewer incidents detected by JSO as compared to FHP in the studied period.

Conclusions and Recommendations

Incident durations are used to assess the performance of different incident management strategies. At the same time, the incident timeline has a number of elements, which can give specific inference on the incident management procedure. While it has been a custom for traffic incident studies to focus on clearance duration because of its considered critical nature, the other neglected elements are important in the incident management process. This study focused on investigating incident characteristics that may affect verification and response duration of an incident. Verification and response durations affects the total incident duration and influence the clearance procedure. Also, verification and response durations can act as effective measures for some of the newly introduced incident management strategies, e.g. co-location of incidents responding agencies.

This study was conducted to accomplish two objectives - illustrating factors that affect verification and response duration of incidents and investigating the effect of co-location of agencies on the incident management procedures. For the first objective, the study analyzed hazard based models, one for verification duration and another for response duration. Results from the statistical models underline the diversity of factors that influence the verification and the response duration of an incident. Results suggested that incident type, the percentage of lane closure, number of responders, incidents severity, I-95, I-75, road users, CCTV and day-of-the-week (weekend and weekday) were factors affecting verification duration significantly in both years. Also, response duration is significantly influenced by incident type, the percentage of lane closure, number of responders, moderate severity, time of the day, I-75, Road Rangers and FHP duration in both study periods.

To accomplish the second objective, the study compared results from the models estimated from the data before and after starting operations of the co-located facility. The comparison of the estimated probabilities graphs and the test of the hypothesis for the difference between coefficients of models between the before and after suggested a difference between the durations before and after co-location of the agencies. The verification duration suggested no significant improvement and a slight decline in the verification of incidents depending on the variables, for instance roadway (I-95) and off-peak hours. Results for the response duration showed improvements gained after the operations of the co-located TMC.

Despite all the efforts to account for the effects of co-location, the study was limited by the fact that actual co-operation between the co-located agencies could not be measured. As stated by a previous study by USDOT-ITS (2000) co-location of incident management agencies in a TMC does not imply cooperation among them. This might have played a part in the results obtained for the verification duration, which does not suggest improvement. There might also be temporal changes that are accounted for in this study. Despite the limitations, this study can be used by incident management agencies to pave ways in assessing incident management procedures and assist in improving parts of the incident timeline, which may be critical to the incident management procedures.

CHAPTER 3 : PAPER 2
Evaluating the impact and clearance duration of freeway incidents

Paper 2 was submitted on 9th April, 2018 and is under review for publication in the International Journal of Transportation Science and Technology. The same paper was presented during the 97th Transportation Research Board annual meeting in January 2018 in Washington, D.C.

Introduction

Traffic incidents are estimated to cause 25% of all non-recurring congestion in the country (U.S.DOT Federal Highway Administration, 2017). In 2014 alone, the United States experienced 42 hours of delay per person during peak hours and the nation lost about 160 billion USD in total due to congestion (Schrank., Eisele., Lomax., & Bak., 2015). Incident management agencies around the country are working on improving strategies to ensure safe and quick clearance of traffic incidents. Initiatives that are being taken include advancing the use of Intelligent Transportation Systems (ITS), having better coordination amongst incident responders and using on-the-road help services such as what is known as Road Rangers in Florida. Some agencies are implementing strategies such as developing pre-planned diversion routes, usage of ITS to verify incidents and co-location of the Traffic Management Center (TMC) with other incident response agencies (PB Farradyne, 2006). It is worth mentioning that all of the Florida Department of Transportation (FDOT) districts are aggressively implementing incident management practices to meet the 90-minute goal of the Open Roads Policy (USF, 2005). This policy requires all incident management agencies to have an objective of clearing incidents within 90 minutes of the arrival of a first responder at the incident scene (FDOT, 2014).

In order for these efforts to realize their intended goals, it is critical to have reliable information on the incident duration. Incident management agencies require precise incident duration estimates to give accurate information to road users, apply the correct incident management measures and assess the effectiveness of incident management strategies (Margiotta, Dowling, & Paracha, 2012). The traffic incident timeline starts when the incident occurs to the time when normal flow returns (Amer et al., 2015). The incident duration comprises four distinct intervals: detection, response, clearance, and recovery (Transportation Reseach Board, 2010). However, there are cases where incidents do not exhibit all intervals of the incident timeline (Smith & Smith, 2001). While most agencies use the incident clearance duration as a performance measure, the duration after which traffic returns to normal is not typically reported. Understandably, as much as it is important to clear the incident scene, it is equally important to get the traffic condition back to normal after the incident occurs. SUNGUIDE, an incident management database used in Florida, consists of data for only the first three incident duration intervals. The duration of the actual impact of an incident (including recovery) is not in the SUNGUIDE database because the incident response staff cannot estimate it on-site. This is most likely the case for other states because most studies analyze incident clearance duration (Chimba, Kutela, Ogletree, Horne, & Tugwell, 2014; Ghosh, 2012; Smith & Smith, 2001) and not the incident impact duration by leaving out the recovery time.

Since most statistical models that explain the effects of various factors on incident duration have considered only the clearance time, there is a need to explore the inclusion of the recovery time to account for the incident impact duration. Therefore, this study is aimed at comparing the statistical model outcomes by using the incident clearance duration and incident impact duration (including recovery time) as response variables. Since the recovery time is not recorded in the SUNGUIDE system, this study first demonstrates a devised approach used to estimate the incident impact duration (including recovery time) for each incident.

Literature review

In this paper, the summary of literature is organized in a thematic structure. It starts by discussing how incident duration has been defined by previous studies and continues by documenting previous efforts in estimating incident recovery time. Then a summary of the literature on previous statistical modeling work is provided, followed by a discussion on the factors that have been used in modeling incident duration in the past.

Definition of incident duration

According to the Highway Capacity Manual (Transportation Reseach Board, 2010), incident duration comprises of four distinct intervals: detection, response, clearance, and recovery. This definition is consistent with the incident timeline (Figure 3.1), which starts when an incident occurs, identifies key interim activities, and ends with traffic returning to normal. There are inconsistencies, however, in the way different studies define the incident duration. Instead of starting at the crash occurrence time (T_o in Figure 3.1), several studies (Junhua et al., 2013; Park, Haghani, & Zhang, 2016; Zhou & Tian, 2012) defined the incident duration from the notification time (T_1). Others considered the incident duration to end when the last responder leaves the scene (Chimba et al., 2014; Chung, 2010; Garib, Radwan, & Al-Deek, 1997; Margiotta et al., 2012) and ignore recovery time as one of the key components of the incident duration. Some of these studies (Garib et al., 1997; Jeihani, James, Saka, & Ardeshiri, 2015; Zhou & Tian, 2012) have admitted the omission of the recovery time and attributed it to difficulty in obtaining the last segment of the incident timeline ($T_7 - T_6$). Only a few studies (Hojati, Ferreira, Washington, Charles, & Shobeirinejad, 2014; Smith & Smith, 2001; Wang, Chen, & Bell, 2005) have considered the recovery time in their analysis of incident duration. These studies derived the recovery time from traffic flow characteristics at the time and location of the incident. The reviewed literature suggests a need for establishing a robust method for estimating recovery time.

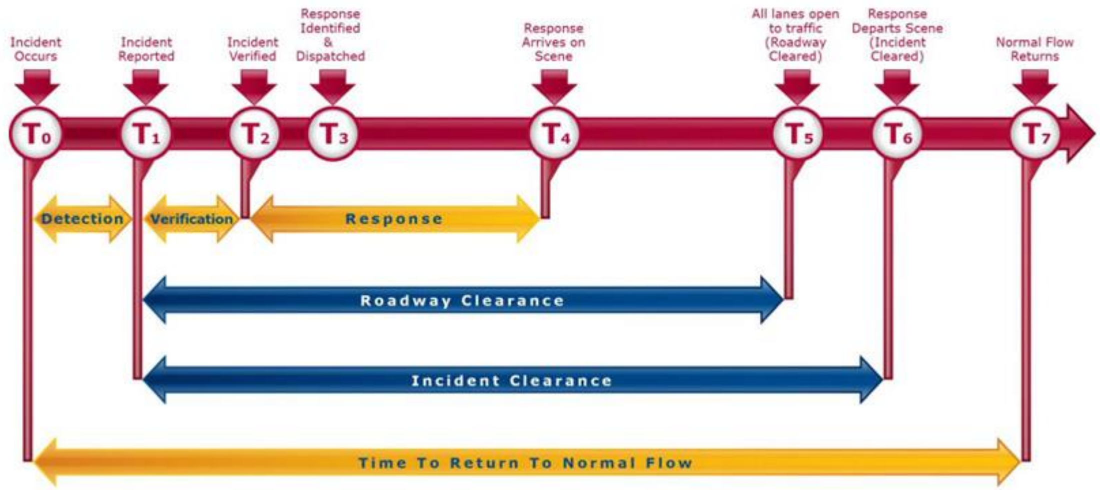


Figure 3.1 Timeline of traffic incident elements (Amer et al., 2015).

Estimation of incident recovery time

Literature review uncovered only a few studies (Hojati et al., 2014; Jeihani et al., 2015; Smith & Smith, 2001; Zeng & Songchitruksa, 2010) which have reported on incident recovery time estimation. Zeng and Songchitruksa (2010) estimated recovery time using travel time for normal flow and during incidents. According to the study, traffic returned to normal (end of recovery duration) when the reported travel time was similar to that on non-incident traffic conditions. The study was limited by the dependence on the accuracy of recorded data, resolution of the temporal data and subjective visual verification of the incident beginning and end times. Hojati et al. (2014) estimated incident recovery time by using speed profiles developed from loop detector data. Results from the study (Hojati et al., 2014) suggested that different incident types had various extents of incident impact duration. Unfortunately, the extraction process produced a small sample size of incidents with complete information to be used for statistical analysis.

Statistical modeling of incident duration

Recent studies have used hazard-based duration models with some variations in assessing incident duration (Chimba et al., 2014; Hojati et al., 2014; Junhua et al., 2013; Nam & Mannering, 2000). One advantage of the hazard-based model is its duration dependence concept which states that time taken to end an incident depends on the time the incident has existed (Washington et al., 2003). For example, Chimba et al.(2014) used accelerated failure time (AFT) model to describe the effect of covariates on the disabled and abandoned vehicle incidents. The model assumed hazard function to follow a log-logistic distribution. The results proposed a need to involve gamma distribution as they were highly influenced by the existing unobserved heterogeneity in the data. Likewise, Hojati et al. (2014) used the AFT model but considered only two distribution alternatives; Weibull and log-logistic. Gamma distribution was later introduced in the Weibull model and a random parameter in the log-logistic model to account for the unobserved heterogeneity.

Factors affecting incident duration

Incident duration is a function of many factors. A study by Ghosh (2012) analyzed factors that affect clearance time and suggested that clearance times were 12% shorter during nighttime hours than daylight hours, and 21% lower on the weekends than weekdays. Winter and absence of exit ramps were associated with longer incident clearance duration. In addition, single-vehicle incidents were cleared 37% sooner than multi-vehicle incidents, incidents on the right shoulder were cleared 31% quicker while incidents on a single lane were removed 28% faster than incidents on multiple lanes.

Another study that evaluated incidents caused by disabled and abandoned vehicles (Chimba et al., 2014) suggested that incident duration can be influenced by the incident notification agency. It was observed that HELP patrol, synonymous to the Florida Road Rangers, were involved in incidents with shorter duration compared to TMC operators, law enforcement agencies, and the public. This could imply that reporting entities other than the road patrol crew would report incidents when they deem to be critical while the Road Rangers might have reported all incidents regardless of severity.

Furthermore, a study by Zhang et al. (2012) analyzed large-scale incidents that were characterized by the incident duration of more than 2 hours. The study indicated that crashes, vehicle fire, the number of vehicles involved in an incident, rain, and peak hours were associated with longer incident durations for small-scale incidents. However, large-scale incidents had longer durations when an incident occurred within a work-zone, on a curved roadway segment, and during morning peak hours. The large-scale incident duration is 15% longer on curved roadway segments than on straight segments, and 13% longer when the incident is associated with secondary crash compared to when not related to secondary crashes.

Study objectives

The aim of this study is to analyze incident impact duration (including recovery time) and its association with temporal, spatial, and other environmental factors. The incident impact duration is thus defined as the time from incident occurrence as recorded by the incident managers to when the affected operational characteristics of a roadway segment return to normal. This duration can be either longer or shorter than the incident clearance duration depending on the incident characteristics. Although previous studies (Chung, 2010; Hojati et al., 2014; Smith & Smith, 2001) have described recovery time as the period after the recorded clearance duration as shown in Figure 3.1, there are cases where traffic operations return to normal before the incident is cleared such as incidents involving abandoned vehicles. Results from the statistical model of incident impact duration will be compared to those from the model on the incident clearance duration as recorded in the incident management database. A discussion of the impact of factors as established by both models will be done in order to provide an understanding of the differences that can be observed when using different incident durations. Moreover, the model evaluation will be performed so as to assess the predictive accuracy resulting from using these two types of incident durations. It is expected that the study will provide additional knowledge to incident management practitioners when selecting incident duration data to be used in the evaluation of incident management strategies.

Methodology

Data description

The incident data were obtained from SUNGUIDE database, a repository of incident information for the FDOT. The study used 2015 and 2016 incident data for Interstate 95 section that crosses the Duval County in Jacksonville, Florida. The dataset included 8,248 incidents with critical incident information such as detection duration, response duration, and spatiotemporal attributes of the incident. All types of incidents were included in the dataset; crashes, vehicle problems (disabled or abandoned vehicles), and hazards such as debris. The study also employed speed data based on BlueTOAD devices. These are Bluetooth signal receivers which read the media access control (MAC) address of the active Bluetooth device in a vehicle. The devices act in pairs by recording the time when a vehicle passes both devices. The recorded time when passing each device is used to deduce travel time of the vehicle between a pair of devices. The speed of the vehicle is calculated from the obtained travel time and a known path distance between the devices. The historical speed data (15-minute speed data) were collected for a three-year period (2014, 2015, and 2016), and for both I-95 northbound and southbound directions.

Extraction of incident impact duration

Figure 3.2 shows a procedure used to estimate incident impact duration (including recovery time) by relating available incident data to the speed data. Each incident was matched to the specific BlueTOAD device pairs located on the roadway segment where an incident occurred in order to retrieve speeds based on the geographical coordinates of devices and incidents, and date and time of the incident. Historical speed data from 2014 to 2016 for the device pairs with matched incidents were used to establish recurrent speeds measured on the devices by averaging the speed for each 15 minutes, for each of the seven days of a week. Figure 3.3 shows a speed profile of Thursdays for a specific BlueTOAD pair, and the speeds during an incident within the pair's segment. As illustrated in Figure 3.3, a confidence interval of one standard deviation was used to define upper and lower bounds of the average speeds to account for recurrent speed variations. For the incidents that were successfully matched to the devices, the BlueTOAD reported speeds at the segment of the incident occurrence were tracked from the time of the incident detection to the time when the traffic flow returned to normal (i.e., speed gets back within speed profile bounds). The duration from incident detection to the return to normal speeds was recorded as the incident impact duration. A similar procedure was repeated for all incidents contained in the dataset.

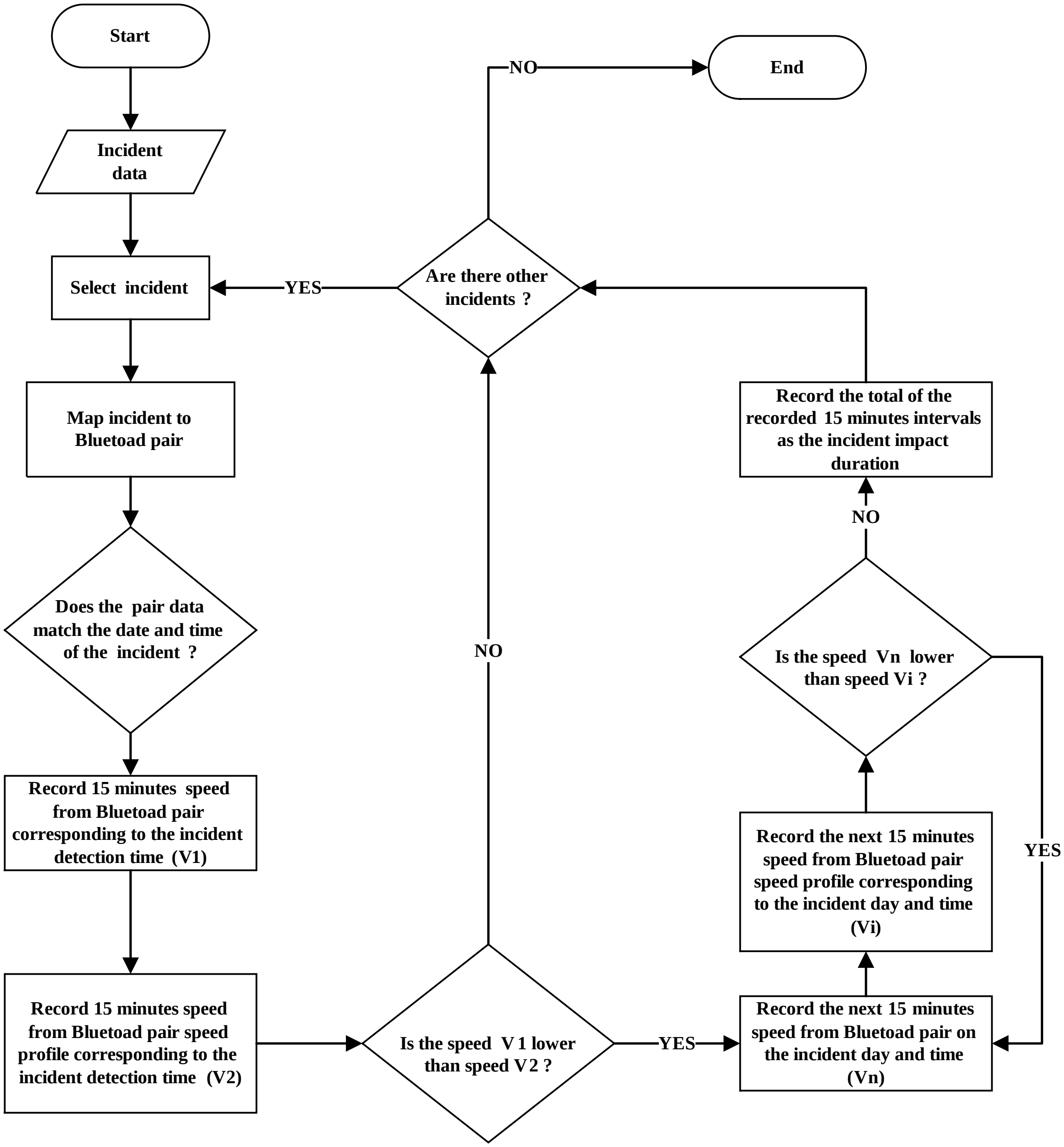


Figure 3.2 The flowchart for the process of extracting incident impact duration

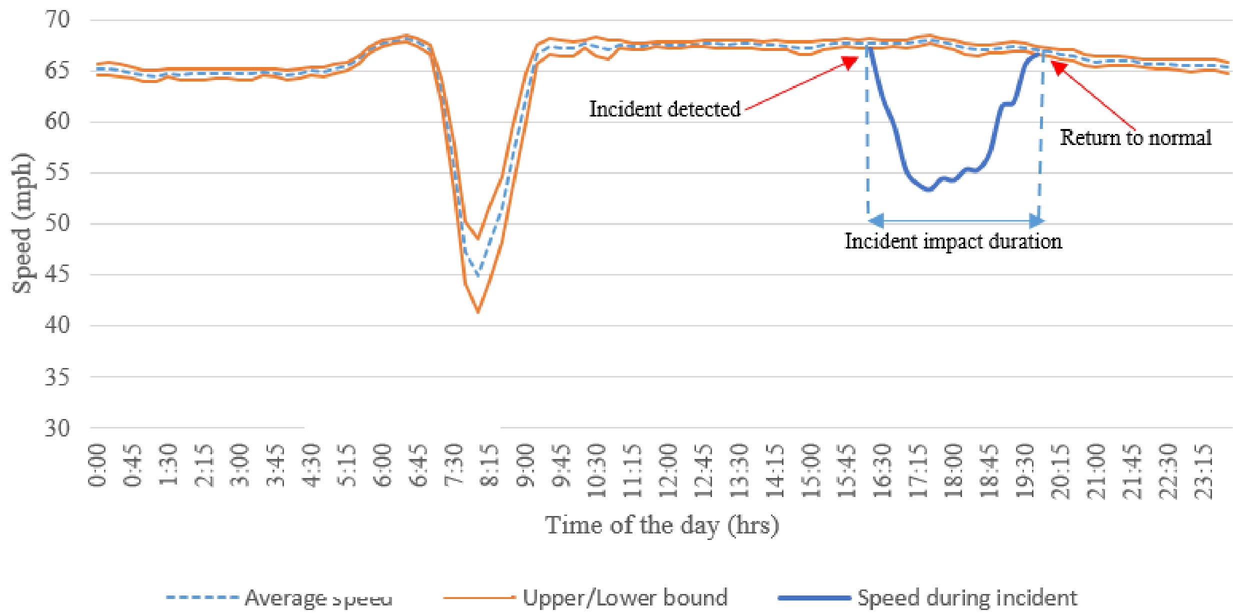


Figure 3.3 Estimation of incident impact duration from speed profiles

Model formulation

In order to study duration data, hazard-based models were employed to describe the conditional likelihood of an incident ending at some time T given that the duration has continued until time t. The hazard-based models consider T as a random variable time and t as a specific time. The cumulative density function and the density function are represented in Equations 3.1 and 3.2, respectively. In Equation 3.1, P represents the probability of the incident to survive at time T. The hazard function is described by Equation 3.3 that shows the conditional probability for an event to occur at time T given that it has not occurred until time t (Washington et al., 2003).

$$F(t) = P(T < t) \tag{3.1}$$

$$f(t) = \frac{dF(t)}{dt} \tag{3.2}$$

$$h(t) = \frac{f(t)}{[1-F(t)]} \tag{3.3}$$

For the hazard-based models to take account of the covariates, accelerated failure time model is used. This hazard model type assumes that covariates rescale time directly in the survivor function. The accelerated failure model hazard function is written as Equation 3.4. The $h_o(t)$ denotes the baseline hazard function, X is a covariate vector, and β is a vector of estimable parameters (Washington et al., 2003).

$$h(t|X) = h_o[tEXP(\beta X)]EXP(\beta X) \tag{3.4}$$

For the applied accelerated failure time model, there is a need to assume a particular shape for the hazard rate. In this study three shapes, Weibull, Weibull with gamma heterogeneity, and log-logistic distributions, were examined.

To investigate the accuracy of model predictions, mean absolute percent error (MAPE) for both, incident impact duration model and incident clearance duration model is calculated. The index is calculated using Equation 3.5, where the actual value of the *ith* observation is represented by A_i while P_i denotes the predicted value of the *ith* observation (Chung & Yoon, 2012). The lower the MAPE the better the accuracy of the model (R. Li & Shang, 2014).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_i - P_i}{A_i}\right| \tag{3.5}$$

Model variables

Two models were developed – one using the incident impact duration (including recovery time) and another using the incident clearance duration as dependent variables. The spearman's test for correlation (r_s= 0.144, p=0) meant the monotonicity characteristic between incident impact duration and incident clearance duration was significantly weak at 95% level of confidence. As for the independent variables, two variables – number of responders and percentage of lane closure were considered to be continuous variables. All other variables including detection method, shoulder blocked, time-of-day and season of the year were modeled as categorical variables. The variable for TMC was categorized into old and new facility. The new facility that started operating in the beginning of 2016 represents the change in the layout of the TMC facility that manages incidents on Interstate-95, from a stand-alone TMC building (old) to the TMC operations co-located with other response agencies such as the Florida Highway Patrol (FHP). A multicollinearity test using variance inflation factors (VIF) suggested absence of collinearity between the investigated independent variables.

Results

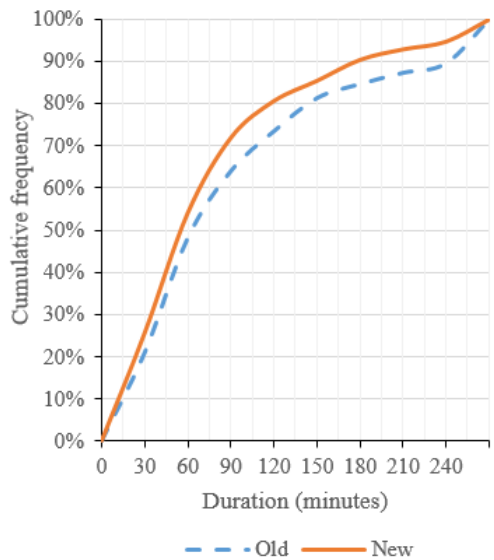
Descriptive statistics

The first step of analysis was estimating incident impact duration (including recovery time) for 8,248 incidents using the algorithm shown in Figure 3.2. Some incidents were not matched to any BlueTOAD devices because of either the absence of active devices near the incident scene or missing geographical coordinates in the incidents database, or lack of collected speed data in the BlueTOAD database during the time of the incident. Also, incidents with incomplete duration data were discarded from the analysis. Estimation of the incident impact duration was successful for only 1,793 incidents, and this subset of data was used for statistical modeling. The incident impact duration extraction process is observed to produce a small sample of incidents, a challenge that was also observed in the study by Hojati et al. (2014). Table 3.1 shows the descriptive statistics of all independent variables used in the model.

Table 3.1 Independent variables for incident duration model

Variables	Categories	Count	Share (%)	Mean impact duration (mins)	Mean clearance duration (mins)
Incidents attributes					
Event type	Crash	664	37%	115	72
	Vehicle problems	1,047	58%	90	21
	Hazards	82	5%	109	20
Detection method	On-road services	1,595	89%	99	38
	TMC	198	11%	111	51
Shoulder blocked	No	841	47%	100	35
	Yes	952	53%	99	44
% of lane closure	Continuous variable			100	40
Incident severity	Minor/Moderate	1,663	93%	96	36
	Severe	130	7%	148	90
Secondary crash involved	No	1,541	86%	88	37
	Yes	252	14%	174	53
Temporal attributes					
I-95 direction	South	835	47%	91	39
	North	958	53%	108	40
Time of day	Peak hour	1,520	85%	95	39
	Off peak hour	273	15%	129	41
Season of the year	Spring	504	28%	95	36
	Summer/Fall	1,289	72%	102	41
Lighting condition	Day	1,716	96%	99	38
	Night	77	4%	122	86
Day of the week	Weekdays	1,441	80%	99	38
	Weekends	352	20%	106	46
Agency operations					
TMC facility	Old	750	42%	116	39
	New	1,043	58%	89	40
Number of responders	Continuous variable			100	40
Emergency Medical Services (EMS)	Present	111	6%	141	82
	Absent	1,682	94%	97	37
Towing involved	No	1,553	87%	98	35
	Yes	240	13%	114	73

Crashes constituted 37% (Table 3.1) of all incidents, and had the mean duration of 115 and 72 minutes for impact and clearance durations, respectively. As shown in Table 1, disabled and abandoned vehicles constituted the majority of incidents (58%) while hazards constituted only 5% of total incidents. About 72% of incidents occurred during summer and fall, while 28% of incidents occurred in the spring season. This can be highly influenced by unequal number of months in the seasons of the year. It is evident that incidents had longer impact durations (including recovery time) when served by the old TMC (Figure 3.4a). Figure 3.4b suggests that there is not much difference in the number of incidents for different incident clearance durations with respect to the TMC facility (old or new).



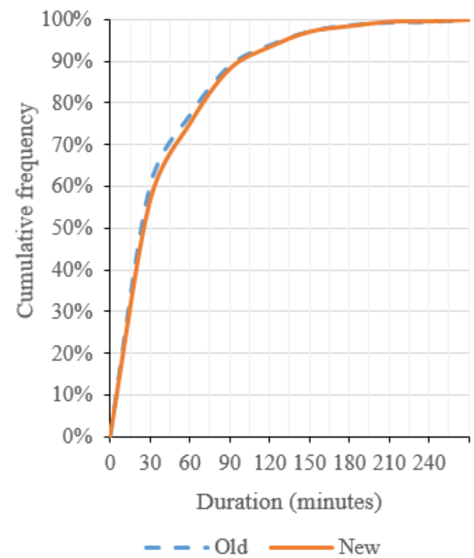
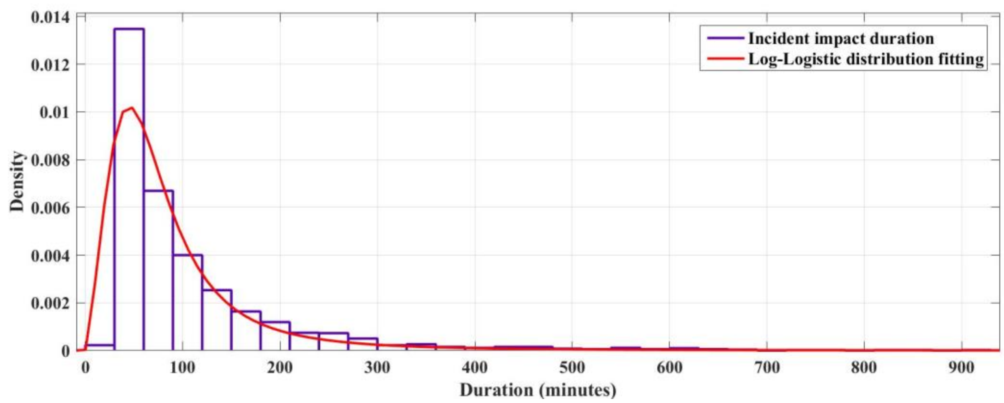


Figure 3.4 Distribution of (a) incident impact duration and (b) incident clearance duration with respect to TMC facility

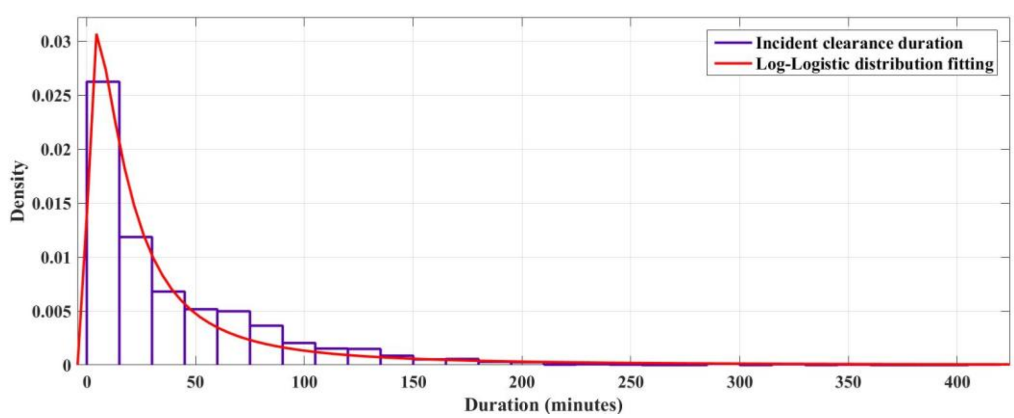
Model results

Choice of the model with the best fit

The first step of statistical modeling was to determine the best hazard function from three distributions: Weibull, Weibull with gamma heterogeneity, and log-logistic distribution. The log-logistic distribution is preferred to lognormal distribution based on results of previous research (Chimba et al., 2014; Hojati et al., 2014; Nam & Mannering, 2000). The shape of the lognormal distribution, however, is similar to that of log-logistic distribution and may produce similar results (Kleinbaum & Klein, 2005). The Weibull with heterogeneity distribution was explored in order to assess the effects of unobserved heterogeneity. The best of the three models was selected based on the Akaike information criterion (AIC). The model with the lowest AIC value is considered to provide the best fit of the data (Kaabi et al., 2012). For the incident impact duration model, the AIC values were 19,694, 19,267 and 19,111 for Weibull, Weibull with gamma heterogeneity, and lo-logistic distributions, respectively. The AIC values for the incident clearance duration model were 15,755, 15,753 and 15,707 for Weibull, Weibull with gamma heterogeneity, and log-logistic distributions, respectively. Since the log-logistic distribution yielded the lowest AIC values for both the models, it was considered to provide the best fit. Figure 3.5 shows the log-logistic distribution fitting for the model response variables.



(a)



(b)

Figure 3.5 Log-logistic distribution fitting for (a) incident impact duration (b) incident clearance duration

From this point forward, therefore, the discussion will be on the results from the log-logistic distribution only. Table 3.2 provides a summary of the log-logistic distribution models for the two response variables, incident impact duration and incident clearance duration. For each model, the first column of the results shows the fitted model coefficients based on Equation 3.4. This study adopted a 95% confidence level to test the significance of the effects of model variables on incident duration. Therefore, a *p*-value of 0.05 is a threshold for the significance level. A column that depicts the percentage (%) change shows the difference in the percentage of the incident duration of a corresponding factor-level compared to the base factor-level. For example, for event type factor, the crash is a base level. A -17.6% change shown in Table 3.2 for vehicle problems factor is the difference in incident impact duration between vehicle problems and crashes. The following sections provide a more detailed discussion of the results presented in Table 3.2.

Discussion

Incident attributes

When compared to crashes, model results presented in Table 3.2 show a decrease of 18% and 69% in incident impact duration and incident clearance duration respectively for vehicle problems. Similarly, there is a 15% and 75% decrease in impact duration and clearance duration respectively when hazards are compared to crashes. Incident management procedures for crashes require a longer time for the police investigation and for emergency treatment to the injured parties in case of severe crashes. Additionally, crashes lead to longer recovery time due to their type of management strategies, which sometimes involve lane closures and route diversion.

Incidents detected by the TMC have a longer impact duration (5.8%) and clearance duration (40.5%) than incidents that are detected by on-the-road help services (Table 3.2). It is possible that because the on-the-road help services are already on the scene, they can respond quickly. The longer durations for incidents detected by the TMC staff might be attributed to the delay in information dissemination, response dispatch delays, and difficulty in getting to the incident scene due to deteriorated traffic conditions caused by the incident.

Table 3.2 Model results for the log-logistic distribution

		Incident impact duration			**Incident clearance duration**		
Variables	Categories	Estimates	*p*-value	% Change	Estimates	*p*-value	% Change
Incidents attributes							
Event type	Crashes						
	Vehicle problems	**-0.194**	0.000	-17.6	**-1.177**	0.000	-69.2
	Hazards	-0.158	0.054	-14.6	**-1.389**	0.000	-75.1
Detection method	On-road services						
	TMC	0.056	0.281	5.8	**0.340**	0.000	40.5
Shoulder blocked	No						
	Yes	0.058	0.103	5.9	**0.270**	0.000	31.0
% of lane closure	% of lane closure	0.339	0.027	40.3	-0.321	0.136	-27.4
Incident severity	Minor/Moderate						
	Severe	**0.324**	0.000	38.2	**0.273**	0.022	31.3
Secondary crash	Yes						
	No	**-0.631**	0.000	-46.8	-0.101	0.125	-9.6
Temporal attributes							
I-95 Direction	Northbound						
	Southbound	-0.049	0.131	-4.8	-0.010	0.825	-1.0
Time of day	Off-peak hour						
	Peak hour	**-0.245**	0.000	-21.7	0.118	0.065	12.6
Season of the year	Spring						
	Summer/Fall	-0.004	0.908	-0.4	0.068	0.186	7.1
Lighting condition	Day						
	Night	**0.184**	0.027	20.2	**0.698**	0.000	101
Day of the week	Weekday						
	Weekend	-0.050	0.220	-4.9	**-0.123**	0.035	-11.5
Agency operations							
TMC	Old						
	New TMC	**-0.160**	0.000	-14.8	**-0.139**	0.005	-13.0
Number of responders	Number of responders	0.006	0.822	0.6	**0.409**	0.000	50.5
EMS	Absent						
	Present	-0.056	0.650	-5.4	**-0.799**	0.000	-55.0
Towing involved	No						
	Yes	-0.006	0.918	-0.6	**0.254**	0.004	28.9
	Constant	5.145	0.000		2.952	0.000	
Model evaluation							
Log(scale)		-0.950	0.000		-0.597	0.000	
Scale		0.387			0.550		
AIC		19,111			15,707		
MAPE		0.540			1.120		

Notes: Bold values show significant estimates at 95% level of confidence

Both models suggest that shoulder blockage leads to longer incidents duration (5.9% and 31% for impact and clearance duration, respectively) than when there is no blockage. This finding indicates that even if the lanes are cleared, leaving the vehicle on the shoulder after the incident can affect recovery time. The analysis does not specify shoulder blockage – inside or outside shoulder - because of the high correlation between shoulder position (i.e., un-blocked shoulder position) and a variable for shoulder involvement. It would have been interesting to use this distinction in the analysis to determine whether the inside shoulder blockage leads to significantly longer durations than the outside shoulder blockage. Anecdotal observations suggest that greater impact is expected for left shoulder blockage compared to the right shoulder blockage.

To illustrate the definition of percentage of lane closed, for a four-lane freeway, closing one lane is considered as 25% of the lane closure. Expectedly, the incident impact duration increases with the increase in the percentage of the lane closure. If more lanes are closed (higher percentage of lane closure), the effect of closed lanes can extend much further upstream of the incident scene, thus increasing recovery time. Contrary to expectations, the results suggest a decrease in incident clearance duration with increased lane closure percentage. It is possible that incidents that result in more lane closures are given preference in dispatching first responders. This observation deserves further investigation to decipher if there are any confounding factors that might not have been considered in the model.

Severe incidents have 38% longer incident impact duration and 31% longer incident clearance duration than minor/moderate incidents. Severe incidents can lead to longer recovery duration because of longer clearance procedures, which greatly affect conditions in the upstream traffic. For cases where a primary incident caused a secondary crash, longer durations were observed compared to incidents that did not cause secondary crashes. The impact of secondary crashes is significant for the incident impact duration (47%) but not for incident clearance duration (10%).

Temporal attributes

Incidents that occurred during peak hours had 21.7% shorter impact duration than incidents during off-peak hours. Previous studies by Li (2017) and Zhou and Tian (2012) observed shorter incident durations during peak hours, and attributed the finding to the conscious efforts of management agencies in dealing with incidents that occur during peak hours. For example, because of the known threat of incidents during peak hours, there is extra attention given to the incidents and responding agencies are located closer to crash hotspots. Moreover, during peak-hours, it does not take long for vehicle speeds to return to normal. This is because normal speeds during this period are usually low as a result of recurrent traffic congestion.

At night, incidents have a longer impact and clearance durations. Although this finding is unexpected, the result is similar to that by Nam and Mannering (2000). A possible explanation can be, at night, drivers are able to spot responders on the scene from a distant position and thus reduce speeds to those below one standard deviation of the normal traffic condition. Also, night-time crashes tend to be more severe, hence involving more responders and become complex to execute. It is also possible that fewer responders are on duty at night, resulting in dispatch delays.

According to the results, weekend incidents are associated with significantly longer durations. When compared to weekday incidents, weekend incidents have longer clearance and impact durations by 11.5% and 5%, respectively. Similar to night-time incidents, it is possible that longer durations on weekends are attributed to fewer responders on duty. Interestingly, for weekends, incident clearance duration is longer than impact duration – the one that contains recovery time. This observation suggests that on weekends, due to low traffic demand, most incidents do not cause significant disturbance in the traffic flow. The results suggest that traffic flow returns to normal before the incident is cleared as minor weekend incidents do not cause freeway bottlenecks.

Agency operations

The results indicate that incident impact duration and incident clearance duration decreased as a result of operating from the new TMC. The new TMC is associated with 14% and 13% decrease of incident impact duration and incident clearance duration, respectively. The new facility has FDOT staff, TMC operators, local agency traffic signal operators, traffic monitoring consultants, Jacksonville sheriff representatives, and the FHP personnel under one roof. The shorter durations after the new TMC was operational may be attributed to quicker detection, verification, and dispatch due to seamless information dissemination caused by the co-location of personnel of all incident management stakeholders.

An increase in the number of responders at the incident scene is associated with an insignificant 0.6% increase in the impact duration but a 50.5% increase in the incident clearance duration. Clearance procedures are complex when many responders are at the scene, hence longer incident clearance duration. It is somewhat surprising that the impact duration did not significantly increase with the number of responders. Also, contrary to the expectations, the presence of Emergency Medical Services (EMS) caused a 5.4% and 55% decrease in the incident impact duration and incident clearance duration, respectively. EMS are deployed in incidents that have injured parties. It is possible that responders are dispatched quicker when injuries are involved than for non-critical incidents. For example, it is common for an abandoned vehicle to stay longer on the blocked shoulder than for a severe crash on a blocked lane. Lastly, Table 2 shows that towing operations lead to significantly longer incident clearance duration. In a comparable manner to the studies by Chimba et al.(2014) and Khattak et al. (1995), it is shown that when towing is involved there is a 29% increase in the incident clearance duration compared to when towing is not needed to clear the incident.

Model evaluation

The mean absolute percent error (MAPE) was used to assess the performance of the two models – one that uses impact incident duration as the response variable and the other for the incident clearance duration. A better model yields a lower MAPE value (Chung, 2010). As can be observed from Table 2, the impact duration model has the MAPE value of 0.54 compared to 1.17 for the incident clearance duration model. This indicates that the model that uses impact duration provides better prediction accuracy. If a larger sample of data is available, instead of combining all incidents, it would be interesting to develop a model for each incident type – crashes, hazards, and vehicle problems. It is possible that impact incident duration is a better response variable for one type of incident, and the incident clearance duration is better for another.

Conclusions

Most agencies use incident clearance duration to measure how well incident management strategies work. At the same time, it is the desire of incident management agencies to restore normal traffic conditions as quickly as possible after an incident occurs. While most previous studies have focused on analyzing the incident clearance duration, little has been done to examine the incident recovery duration. This study introduced a measure that was referred to as the incident impact duration, which stands for the duration from the reporting of the incident to the time when traffic condition returns to normal. Depending on the type of incident and prevailing traffic conditions, the incident impact duration could be shorter or longer than the incident clearance duration.

This study was conducted to accomplish two objectives – demonstrate a method of estimating the incident impact duration, and investigate the effects of various factors on the incident impact and clearance durations. For the first objective, the study proposed a technique that uses historical traffic speed data to estimate the incident impact duration. The method uses the speed data reported by the BlueTOAD devices to create a bandwidth of mean speed profiles within one standard deviation for the times when there were no incidents. In the event of an incident, the algorithm checks if the speeds drop below the lower bound (one standard deviation below the historical mean) and tracks the traffic flow speed until it gets back to within the one standard deviation bandwidth. The incident impact duration is computed as the time elapsed from the speed getting below the bandwidth to the time it gets back in the bandwidth.

In order to accomplish the second study objective, two hazard-based models, one for the incident impact duration and another for the incident clearance duration, were developed. Results from the statistical models underline the diversity of factors that influence the impact and clearance incidents duration. Many variables had a similar impact on the durations but differed on the level of significance. Incidents detected through TMC facilities, shoulder closure, night-time incidents, severe incidents, an increasing number of responders and involvement of EMS were associated with the increase of both impact and clearance incidents duration. On the other hand, vehicle problems, hazards, absence of secondary crashes, weekend, and the new TMC operations decreased both durations. Other variables such as; percentage of the lane closure, peak hour traffic condition, summer/fall seasons of the year, and involvement of towing services had conflicting contributions towards impact and clearance incident duration. Discussion on the results provided insight on how these variables differently affect the incident impact and clearance duration.

Finally, the study compared the prediction accuracy of the two models – incident impact duration and incident clearance duration. Considering one criterion, mean absolute percent error (MAPE), the model that used the incident impact duration had a higher prediction accuracy than the one that used the incident clearance duration as the response variable. It is important for future research work to investigate the prediction accuracy using other accuracy measures in addition to MAPE. Moreover, the inclusion of all incidents type in the analysis could be the reason for a low MAPE value, which paves the way for future research to investigate the durations by developing separate models for each incident type.

CHAPTER 4 : PAPER 3

Evaluating the Impact of Incident Timeline Elements on Clearance Duration

Paper 3 was submitted on 16th April, 2018 and is under review for publication in the Journal of Traffic and Transportation Engineering (English Edition)

Introduction

Traffic incidents cause poor operational and safety conditions on roadway networks. It is estimated that 25% of the total traffic congestion in the U.S. is due to traffic incidents (Margiotta et al., 2012). Incidents disrupt normal traffic flow and can result in the formation of long queues on the affected roadways (Zhang, Zhang, & Khattak, 2012). Unfortunately, the occurrence of traffic incidents is unpredictable. Due to the uncertainty of occurrence, traffic incidents cause extra delays in unexpected locations and time (Margiotta et al., 2012). Other impacts of traffic incidents are secondary crashes involving other road users present on the roadway during an incident, and in some cases, incident responders (Smith and Smith, 2001; Wang et al., 2005; Zhang et al., 2012). There is an up to 15% likelihood of a secondary crash to occur due to an initial incident, and the probability increases by 2.8% for every minute a primary incident remains a hazard (Karlaftis, Latoski, Richards, & Sinha, 1999; A. Khattak, Wang, & Zhang, 2012). Therefore, a short clearance duration can reduce the consequences of traffic incidents on safety and operations of a roadway.

A short clearance duration decreases the possibility of an incident from becoming a large scale incident (Zhang et al., 2012). Incidents with short clearance durations have a lower risk of cascading than incidents with long clearance duration (Zhang & Khattak, 2010). Quick clearance reduces the whole incident timeline because clearance duration is the most time-consuming period in the timeline (USDOT-ITS, 2000). As a result of quick clearance, the incident recovery duration can be shortened and decrease the incident induced delays. In fact, other elements of the incident timeline may not be present on every incident, but clearance duration is inevitable (Smith & Smith, 2001). However, duration of incident clearance depends on many factors that are related to the incident. For example, clearance duration of debris on the roadway is not similar to the clearance duration of crashes. For responding agencies to introduce incident management strategies that reduce incident clearance duration, it is essential to understand factors that influence incident clearance procedures.

Most studies have investigated factors that influence clearance duration, ranging from incident attributes to the characteristics of incident responders. For example, Lee and Fazio (2005) observed that length of the clearance duration is highly influenced by the incident management team because it involves activities at the incident scene. Even with an abundance of research on factors that affect clearance time, durations before the incident clearance have been overlooked as factors that influence the clearance duration. Incident elements such as verification time, dispatch duration and travel time of responders can affect the clearance duration. This is because the length of each element of the traffic incident timeline is affected by the preceding elements (Golob, Recker, & Leonard, 1987).

It is the aim of this study to investigate the influence of incident timeline elements before clearance on the extent of the clearance duration. These elements include detection period, verification duration, dispatch duration, and response travel duration. The study will identify the important incident elements in the prediction of clearance duration. In addition to the effect of elements of the incident timeline, this study analyzes the impact of other spatial and temporal attributes on the clearance duration using a Cox regression model estimated using the Least Absolute Shrinkage and Selection Operator (LASSO) penalization method.

Literature review

Clearance duration

There are inconsistencies on the term clearance duration. The FHWA defines "incident clearance duration" as the time between the first recordable awareness of the incident by a responsible agency and the first confirmation that lanes are available for traffic flow (Amer et al., 2015; Owens et al., 2010). However, when the term used is "clearance duration", most studies refer to the period when responding agencies treat victims, close lanes and eventually remove vehicles and debris from the roadway (Ghosh, 2012; Junhua et al., 2013; Li, 2017; Nam & Mannering, 2000; Smith & Smith, 2001). As a result, clearance duration is the most difficult incident element to control because it depends on factors that are unique to individual incidents (Nam & Mannering, 2000). For example, when incidents involve fatalities or hazardous materials, longer clearance times are expected (Nam & Mannering, 2000). A study by Li (2017) observed that the mean clearance duration for hazardous materials is 110 minutes.

Apart from incident type, other factors have been observed to influence the clearance duration. Nam and Mannering (2000) observed longer clearance times during morning and afternoon commuting times. Lee and Fazio (2005) suggested that the average clearance time for peak periods is 78 minutes and traffic crash sites had 20% and 40% shorter clearance times during weekdays than during weekends for both morning and evening peak periods. All these factors were investigated with the aim of understanding and eventually decrease the clearance duration.

Reducing clearance time has the greatest potential for improving overall incident management times (USDOT-ITS, 2000). Clearance duration can decrease when proper resources are dispatched to the incident scene (USDOT-ITS, 2000). For instance, qualities of the first agency to reach the incident scene has a significant impact on the clearance duration (Nam & Mannering, 2000). Because every agency performs different task at the incident scene, their impact on the clearance duration is different. For example, one study reported that on average Highway Safety Patrol (HSP) and Police (148 minutes) spend 173 minutes and 148 minutes on-scene respectively (Li, 2017). Therefore, interagency cooperation among responders is critical to improving incident clearance times (USDOT-ITS, 2000).

Incident elements before clearance

Traffic incident timeline is comprised of sequential phases which are inter-related (Golob et al., 1987). Incident elements before the clearance duration are the detection/reporting, verification, dispatch, and responders travel duration (Amer et al., 2015). Detection or reporting time is the period from the occurrence of an incident to the time an incident is reported to the responding agencies (Junhua et al., 2013). A few studies (Kaabi, 2013; Nam & Mannering, 2000) managed to investigate detection duration but were limited by the determination of the exact time of occurrence of incidents. Nam and Mannering (2000) observed that incidents that occur during morning peak hours have short detection time and longer reporting durations are associated with incidents that involve injuries and fatalities.

Verification duration is described as the period for determination of the precise location and nature of an incident (USDOT-ITS, 2000). According to the FHWA, verification duration starts at the time responding agencies are notified of the incident to when the response is dispatched (Amer et al., 2015). On the other hand, dispatch duration and travel time to the incident scene comprises the response duration (Nam & Mannering, 2000). Dispatch duration is the period from when the incident is verified to when the responders are dispatched while the time responders spend traveling to the incident scene is called response travel duration (Amer et al., 2015). Studies have investigated response duration (Kaabi et al., 2012; Lee & Fazio, 2005; Nam & Mannering, 2000) but not its elements.

Due to the scarcity of literature on the incident elements before clearance duration, it is the objective of this study to investigate effects of elements of the traffic incident timeline on the duration of the clearance procedure. Moreover, the study evaluates how other incident related factors play a part in the length of the clearance procedures. The Cox regression model under the LASSO penalization method is used to identify the factors that are vital to the length of clearance duration. It is expected that the knowledge from this analysis will help incident management agencies when selecting strategies for reducing the incident timeline. Results from this study will show the important incident elements prior to incident clearance, and how they influence the clearance duration.

Materials and methods

Data description

Incident data was retrieved from SUNGUIDE, which is a repository of incident data for the Florida Department of Transportation (FDOT). The data included all incidents that occurred on the freeway network in the Duval County, Florida. The data contained incidents that occurred in Duval County for the period of four years, from 2014 to 2017. Due to missing clearance duration and other elements of the incident timeline, 1180 incidents were analyzed. Incidents in the analysis included crashes, vehicle problems, and hazards. Moreover, the incident data contained other incident attributes such as a number of responders and detection method of an incident.

Cox regression model

Analysis of the impact of variables on the incident duration is achieved through Cox regression model. Cox regression models are semi-parametric hazard-based duration models because they do not make an assumption on the distribution of duration times but maintain a parametric assumption of how explanatory variables influence the hazard function (Kaabi, 2013; Lee & Fazio, 2005; Washington et al., 2003). Equation 4.1 shows the mathematical formulation of the Cox regression model where $h_i(t)$ is the hazard function of the clearance duration t of an incident i, x_i is the covariate of an incident, and β is the covariate coefficient.

$$h_i(t) = h_o(t)EXP(\beta x_i) \tag{4.1}$$

Parameters of the covariate are estimated using the partial likelihood estimation method, which does not consider the baseline hazard in the estimation. The model is based on the ratio of hazards such that the probability of a clearance duration of an incident i ending at time t_i , given that at least one observation exits at time t_i is given as Equation 4.2.

$$\frac{h_i(t)}{h_j(t)} = EXP\{\beta_1(X_{i1} - X_{j1}) + \cdots + \beta_1(X_{i1} - X_{j1})\} \tag{4.2}$$

Hazard ratio

Hazard ratios are calculated to make inference on the results calculated from the Cox regression model. The hazard ratio shows the value of e^{β} where β is an estimate of a variable coefficient (Kleinbaum & Klein, 2005). For dichotomous variables, hazard ratio is the ratio of the estimated hazard with a value of 1 to the estimated hazard with a 0 value while controlling other variables (Lee & Fazio, 2005). The hazard ratio greater than 1 suggests an increase in the hazard due to a covariate, a hazard ratio of less than 1 suggests a reduction in the hazard while a hazard ratio that equals to 1 indicates no significant effect due to the covariate.

Least Absolute Shrinkage and Selection Operator (LASSO)

To tackle the issue of variable selection in incident data with a high number of covariates and obtain the relevant variable, penalized likelihood estimators called LASSO estimators can be applied (Honda & Karl Härdle, 2014). LASSO shrinks some coefficients of a regression model, in this case, Cox regression and sets others to zero (0) to obtain variables with a substantial effect on the outcome (Tibshirani, 1996). This method is one of the recently applied regularization methods, which can automatically and simultaneously select variables and estimate the coefficients (Liu, Zhang, Zhao, & Lv, 2015). The LASSO estimator β^L has to satisfy Equation 4.3.

$$\beta^L = \arg min_\beta \left\{SSE(\beta) + \lambda \sum_{j=1}^{p} |\beta_j|\right\}, \quad \lambda \geq 0 \tag{4.3}$$

Where $\sum_{j=1}^{p} |\beta_j|$ is called the LASSO penalty and β is the covariate coefficient of a Cox regression model. As regularization parameter (λ) increases, the elements of β^L are continuously shrunk towards zero such that some elements will be shrunk to zero and automatically deleted. The LASSO estimators are calculated using iteratively reweighted least squares algorithms for each value of the regularization parameter λ (Zou, 2008). The estimation of regularization parameter for the model is achieved by using cross validation and selecting the regularization parameter that gives the minimum prediction error.

Variables categorization

Most of the variables in the incident data were categorical, for example, the incident type, detection method, severity of an incident and involvement of the ramp. The vehicle problems category described all incidents that are related to the vehicle but that are not crashes including vehicle breakdowns, abandoned vehicles, and vehicle fire. The category for hazards described all dangers present on the roadway that are not vehicles such as debris, flood, and wildlife. Detection methods were categorized into four groups; on road-help services, road users, TMC operations and other methods. On-road help services included all highway-involved services that patrol the roadways, e.g. Road Rangers, Florida Highway Patrol (FHP) and the Jacksonville Sherriff's Office (JSO). Road users described incident information obtained from the motorists through sources such as phone calls and WAZE. TMC operations included CCTV cameras and information from TMC personnel while the other methods category comprised sources such as construction office and FDOT maintenance asset managers.

Continuous variables included the elements of traffic incident timeline prior to clearance duration, i.e. verification, dispatch, response travel duration and the interaction of dispatch and response travel duration. Other continuous variables are the percentage of lane closure and number of responders for an incident. The percentage of lane closure was estimated by dividing the number of closed lanes to the available lanes on the roadway. The percentage ranged from 0% when there is no closed lane to 100% when all lanes are closed.

Results

Descriptive statistics

The mean clearance duration of the analyzed incidents is 37 minutes. Figure 4.1 shows the distributions of all incident timeline elements analyzed in the model. Figure 4.1a shows that a high percentage of verification time (46%) is less than 5 minutes. When comparing Figure 4.1a and Figure 4.1b, it can observed that the verification duration takes longer than the dispatch duration. Figure 4.1b shows that the dispatch duration for a large proportion of incidents is less than 10 minutes. For example, about 65% of incidents have the dispatch duration of less than 2.5 minutes. Figure 4.1c shows that the response travel time duration for most of the incidents is less than 12 minutes. Twenty three percent (23%) of the incidents had the response travel duration of less than 4 minutes whereas 27% of the incidents had the response travel duration between 4 minutes and 8 minutes. When comparing the Figure 4.1d and other Figures (4.1a, 4.1b, 4.1c), it can be observed that the clearance duration takes longer than other incidents, for example, there are incidents with clearance duration of 192 minutes. However, a great percentage of the incidents (45%) were cleared in less than 16 minutes.

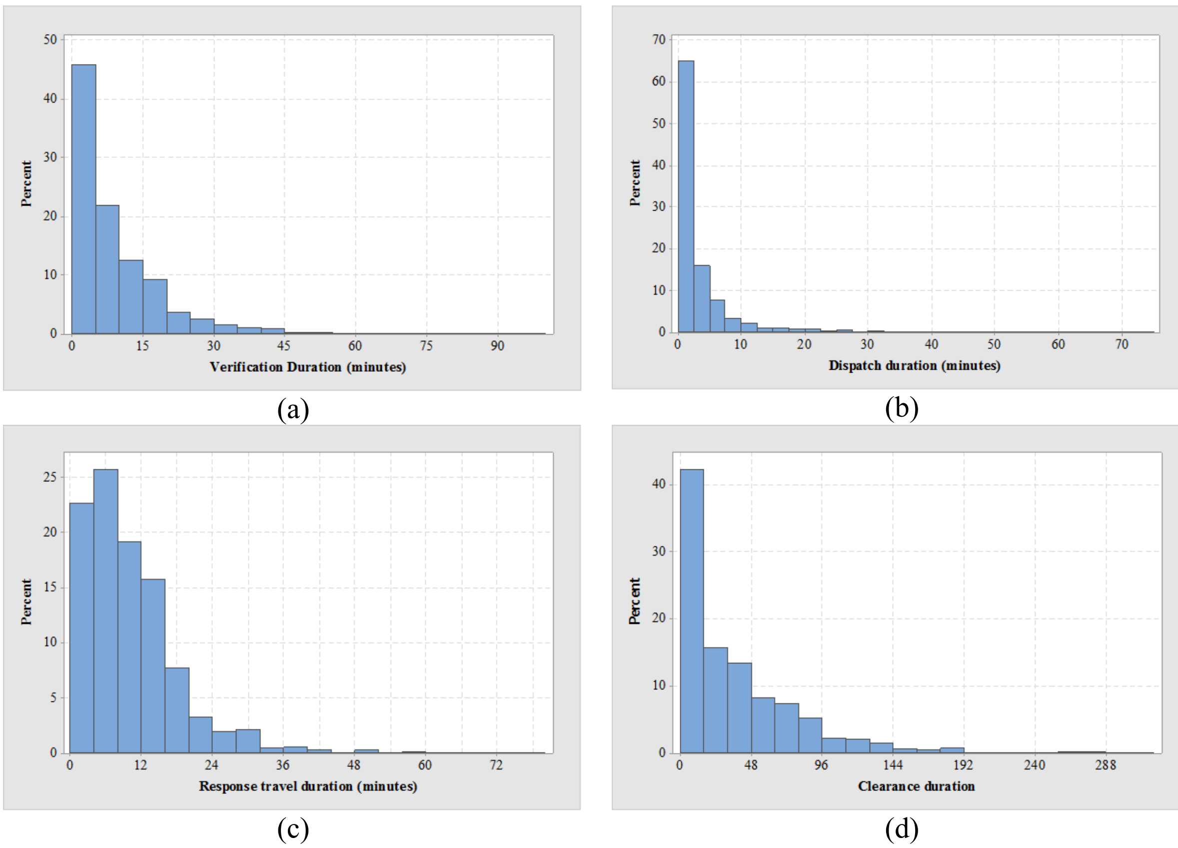


Figure 4.1 Distribution of (a) verification duration (b) dispatch duration (c) response travel duration and (d) clearance duration

Table 1 shows that the mean clearance duration of other types of incidents is less than the mean clearance duration of crashes (46 minutes). Moreover, the mean clearance duration for vehicle problems (29 minutes) is less than that for crashes and longer than the mean clearance duration of hazards (10 minutes). The proportion of incident types suggest that there are more crashes in the data as compared to vehicle problems. This is because that most of the crash data does not contain missing information timeline information as compared to other incidents.

The detection method variable shows that most incidents (67%) are detected by the on-road help services. TMC operations is the second most frequent detection method, which detected 32% of the analyzed incidents. Table 4.1 shows that the average clearance duration for incidents that are detected by on-road help services (36 minutes) is less than that for incidents that are detected by TMC operations. Although there are few severe incidents, their average clearance duration (104 minutes) is longer than moderate and minor incident clearance duration. Interestingly, the average clearance duration between peak and off-peak hours is 36 minutes and 38 minutes respectively. The number of incidents that occur on ramps or close to the ramps consisted of 21% of the incidents and had the average clearance duration of 44 minutes.

Table 4.1 Descriptive statistics of variables associated with clearance duration

Variables	**Description**	**Count**	**Share**	**Mean clearance duration**
Timeline elements				
Verification duration		1180	100%	37
Dispatch duration		1180	100%	37
Response travel duration		1180	100%	37
Incident attributes				
Incident type	Crash	700	59%	46
	Vehicle problems	335	28%	29
	Hazards	145	12%	10
Detection method	On-road services	787	67%	36
	Road users	12	1%	31
	TMC Operations	376	32%	39
	Other methods	5	0%	17
Severity	Minor	624	53%	14
	Moderate	454	38%	53
	Severe	102	9%	104
Percentage of lane closure		1180	100%	37
Number of responders		1180	100%	37
Spatiotemporal attributes				
Season	Spring	306	26%	34
	Summer/Fall	874	74%	38
Time of day	Peak hours	818	69%	36
	Off-peak hours	362	31%	38
Roadway	I-10	123	10%	46
	I-95	482	41%	35
	I-295	482	41%	37
	SR-202	93	8%	31
Ramp involvement	No	928	79%	35
	Yes	252	21%	44

Model results

Table 4.2 presents the estimates of the independent variables for the Cox regression model estimated under the LASSO penalization method. The column for hazard ratio indicates how the independent variables are related to the clearance duration. Two variables (dispatch duration and time-of the day) have an estimate of zero (0), which suggests that the variables are not important to the response variable. Results from the LASSO penalization method also gives the significance of the variable by considering the absolute magnitude of the coefficient.

Table 4.2 Results of the Cox regression model

Variables	**Categories**	**Estimates**	**Hazard ratio**
Timeline elements			
Verification duration		-0.004	0.996
Dispatch duration		0.000	1.000
Response travel duration		0.008	1.008
Dispatch and response travel		0.000	1.000
Incident attributes			
Incident type	Crash		
	Vehicle problems	0.079	1.082
	Hazards	0.761	2.139
Detection method	On-road services		
	Road users	-0.235	0.790
	TMC Operations	-0.067	0.935
	Other methods	0.549	1.732
Severity	Minor		
	Moderate	-1.275	0.279
	Severe	-2.239	0.107
Percentage of lane closure		0.115	1.122
Number of responders		-0.148	0.862
Spatiotemporal attributes			
Season	Spring		
	Summer/Fall	-0.130	0.878
Time of day	Peak hours		
	Off-peak hours	0.000	1.000
Roadway	I-10		
	I-95	0.215	1.240
	I-295	0.086	1.089
	SR-202	0.302	1.353
Ramp involvement	No		
	Yes	-0.199	0.819

Figure 4.2 presents the LASSO results graphically. The magnitude of the estimate is shown on the vertical axis which is a function of the logarithm of lambda (regularization parameter) shown on the horizontal axis. The top horizontal axis indicates the number of non-zero coefficients at the current regularization parameter (Lambda, λ). The colored lines show the effect of each variable in the model. For example, the line labeled number 5, which represent a variable for

hazards shows a line that starts deviating from the horizontal line after deviation of other three lines (1, 2, and 3). The point where the line start deviating marks the regularization parameter at which the variable starts being significant. This occurs as the regularization parameter of the model decreases. When the penalty (regularization parameter) is so high, only a single variable is significant to the clearance duration i.e. severe incident (the right side of the graph). When the reguralization parameter is so low, the model becomes the ordinary least square and includes all variables as indicated by many lines on the left side of the graph. The significance of estimates increases moving from right to left on the horizontal axis (Log Lambda). Figure 4.2 shows that severe incidents (1), moderate incidents (2), hazards (5) are variables that are present in the model even when it has a high regularization parameter. Other variables enter the model as the regularization parameter decreases.

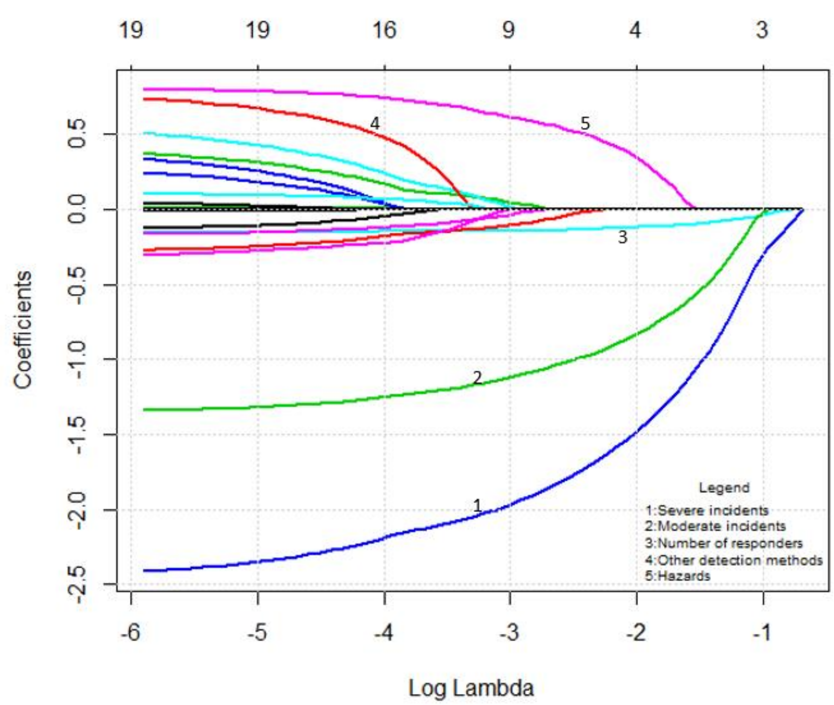


Figure 4.2 LASSO coefficient paths

Discussion

Timeline elements

Verification duration (-0.004) and response travel duration (0.008) have an opposing effect on the clearance duration of an incident. Incidents that take longer to be verified are associated with longer clearance durations. During verification, responding agencies determine attributes of an incident in order to dispatch optimum response. Information such as the type of the incident, number of vehicles involved, and the precise location of incident are confirmed during this period. As a result, incidents that require longer verification time due to many attributes, e.g. crashes have longer clearance durations than incidents with fewer attributes, e.g. debris on the roadway.

Results on Table 2 show that dispatch duration has an insignificant impact on the clearance duration of an incident. Dispatch duration depends on the line of communication and coordination between the responding agencies. For example, the dispatch of co-located response agencies is expected to be quicker than dispatch centers using other methods of communication e.g. phone calls. In most cases, dispatch duration is the shortest period in the traffic incident timeline.

The increase in response travel duration (0.008) is associated with short clearance duration. Incidents that occur where or when it is possible for responders to arrive quickly have long clearance durations. Quick arrival to an incident scene can prevent worsening of the condition at an incident scene. Unfortunately, travel time of responders can be affected by traffic condition, e.g. congested and un-congested. It may take longer for responders to arrive at the incident scene during congested traffic periods than during un-congested traffic condition. However, most incidents that occur during congested traffic conditions (i.e. peak hours) are not as severe as incidents during un-congested conditions. Although incident responders arrive quicker at the incident scene during un-congested condition, the clearance duration is long because most of the incidents are severe and require long clearance durations.

Incident attributes

Table 4.2 shows that incident type is important to the length of the clearance duration. Vehicle problems variable has a hazard ratio of 1.082, which suggests that its clearance duration is longer than that of crashes. In most cases, the disabled and abandoned vehicles are left on the scene for longer periods because of their clearance procedures. Table 4.2 shows that clearance duration of hazards is shorter than clearance duration of crashes. Clearance of crashes involves time-consuming procedures that are related to the safety of individuals involved in the incident in case of injuries, protection of the incident scene in case of fatalities and law enforcement practices.

Detection method variable is significant to the clearance duration because the LASSO estimates of its categories are not equal to zero. The hazard ratio of the road user variable (0.790) suggests that the clearance duration of incidents that are detected by the road users are longer than incidents detected by the on-road help services. Incident information from road users through phone calls or WAZE are not always accurate as compared to on-road help services. When incidents are detected by the TMC operations, the clearance duration is longer as compared to when detected by on-road help services. For example, detection using CCTV cameras lead to longer clearance duration than on-road help services because the presence of on-road help services at the incident scene can help manage the incident scene as early as possible. Other methods of detection lead to shorter clearance durations as compared to the on-road help services. Detection method results show the importance of effective detection systems is not only for the detection and verification period but clearance duration as well.

The LASSO estimates (Figure 4.2) suggest that severity of an incident is the most important factor for the clearance procedure of an incident. Both moderate and severe incidents lead to longer clearance durations than minor incidents. Severe incidents are associated with injuries and fatalities; hence require carefully executed procedures to ensure the safety of individuals involved in the incidents. Moreover, other procedures related to law enforcement and towing services increases the clearance duration. The increase in the percentage of lane closure is associated with quick clearance of an incident. Incidents with many responders (-0.148) have longer clearance durations. Many responders are expected to be present for incidents that are severe and require complex procedures in the clearance of incidents such as severe crashes.

Spatiotemporal attributes

Table 4.2 shows that the hazard ratio for the summer/fall season (-0.130) is less than one. The clearance duration of incidents is longer during this period of the year as compared to the spring season. This may be influenced by the number of days with inclement weather during the summer/fall season than during the spring season. In Florida, rains, storms, and hurricanes characterize summer and fall seasons. It is expected that during inclement weather, number of crashes increases as compared to normal weather days. These type of incidents combined with the poor weather conditions for incident responders to execute clearance procedures may be the reason for longer clearance duration during summer/fall season.

The LASSO estimate for the time of the day variable was zero suggesting that it is not a significant factor for the clearance duration of an incident. Although, it is expected that the clearance duration of an incident during peak hours to be longer than off-peak hours due to constraints surrounding the incidents, the model results suggest a similar effect between the two categories. During off-peak hours, the number of responders on duty for most of the agencies is less than that during that during off-peak hours e.g. nighttime. Also, it is a practice of responding agencies being ready and focused on dealing with any incident during peak hours as compared to off-peak hours.

Results on Figure 4.2 and Table 4.2 suggest that the variable for the roadway is important to the clearance duration. The hazard ratio for all roadways is more than one (1) when clearance duration of incidents of a roadway is compared with clearance duration of incidents on I-10. Incidents that occur on I-95, I-295 ad SR-202 have shorter clearance durations as compared to incidents that occur on I-10. It is not yet clear on what spatial aspects influence such a disparity between clearance durations on these freeways. Table 4.2 shows that when incidents occur on ramps, the incident clearance duration is longer than when it occurs in basic segments.

Conclusions and Recommendations

Many researchers and agencies have used elements of a traffic incident timeline in examining response programs. Specifically, most research has been on the clearance duration due to its importance in the traffic incident timeline. Clearance duration is ever-present in any incident, and in most cases, it is the longest duration of the incident timeline. With an abundance of research focused on analyzing the impact of various factors related to the incident such as responding agencies and percentage of lane blockage, investigation of the association between other incident elements and the incident clearance has been overlooked.

This study was conducted to investigate the influence of the elements of traffic incident timeline prior to the clearance duration. The elements of traffic incident timeline include the detection, verification, dispatch, and response travel duration. In addition to the elements of the incident timeline, the study analyzed the effect of other spatiotemporal and agency attributes that have an impact on the clearance duration. The study used Cox regression model that is estimated using the LASSO penalization method to obtain the significant variables to the clearance duration of an incident. The LASSO penalization method has the advantage of estimating the coefficients of the covariates and selecting the significant variables at the same time. In addition, the method accounts for the multicollinearity that is related to the investigated variables.

Results show that two model variables, dispatch duration and time of the day, are not significant to the incident clearance duration. Other variables were observed to affect the clearance duration in different ways and magnitudes. A longer response travel duration, higher percentage of lane closure, vehicle problems, and hazards have quick clearance durations. A longer verification duration, detection of an incident by road users and TMC operations, severe incidents, summer season and involvement of ramps are associated with longer clearance durations.

Although the results obtained from this study have varying implications on the clearance procedures, the study had some limitations. The estimation method did not involve analysis on the effects of the unobserved heterogeneity on the clearance duration. The study did not analyze the detection and notification duration of an incident due to difficulty in estimating and recording the exact time of incident occurrence. Future research should focus on investigating spatial characteristics that may be influencing the incident clearance duration such as effects of roadways and land use. Finally, results from the study can help responding agencies single out areas of improvement to achieve effective incident management systems.

CHAPTER 5 : OVERALL CONCLUSIONS AND RECOMMENDATIONS

Overview

In in order to manage traffic incidents safely and quickly, transportation agencies continuously introduce and test new strategies for improving incident management. This thesis evaluated the impacts of incident management strategies on the incident timeline. An effective strategy decreases the length of an incident timeline. The incident timeline consists of elements such as detection, verification, dispatch, response travel, clearance, and recovery duration. Therefore, the analysis of the incident timeline has to focus on specific elements of the incident timeline and their association with the incident management strategy.

Co-location of incident responders

Using the newly constructed RTMC in Jacksonville, Florida, this thesis assessed the effects of co-location of incident responders. The new RTMC facility has the responding agencies i.e. Road Rangers and FHP operating under one roof. This strategy is expected to improve communication and coordination between agencies. Reduction of the incident verification and response durations can reflect the effectiveness of co-location strategy. Hence, the study analyzed the impact of co-location by comparing the verification and response duration of incidents in the two (2) years period before co-location and two (2) years period after the co-location. Because of this strategy, significant improvements were observed in the response duration. Analysis of the verification duration did not suggest significant changes between before and after co-location.

Incident impact duration

This thesis analyzed the incident duration that includes the recovery duration. Because of the limitations in the estimation of recovery duration, this study proposed a method to estimate the incident duration that includes the recovery duration using traffic operation characteristics i.e.

speed. Incident impact duration was the term given to describe the incident duration that includes recovery duration. The incident impact duration was analyzed using hazard-based models. Similarly, the incident clearance duration was analyzed in order to deduce the difference between the two durations when analyzing incidents and response measures. Results indicate a significant difference between the incident impact duration and incident clearance duration with respect to incident attributes such as the incident type, time of an incident and incident severity.

Clearance duration

This study investigated effects of the elements of traffic incident timeline prior to clearance on the clearance duration. Elements of the traffic incident timeline before the clearance duration include the detection, verification, dispatch, and response travel duration. This part of the analysis used a Cox regression model that was estimated using the Least Absolute Shrinkage and Selection Operator (LASSO). Apart from the impact of the verification, dispatch, and response travel duration on the clearance duration, this study analyzed effects of other factors on the clearance duration. Results indicate that the verification and response travel duration have a significant impact on the clearance duration. Conversely, the dispatch duration has no significant impact on the clearance duration.

Limitations of the Study and Recommendations for Future Work

Analysis of the traffic incident timeline did not include the detection or reporting time of an incident because of the limitations in recording and estimating the actual time of incident occurrence. There is an opportunity for future research work that will assist responding agencies in estimating the detection/reporting time. Estimation of the reporting time will enable responding agencies to improve the analysis on the effectiveness of incident detection methods such as CCTV and WAZE.

Work zones or construction sites were not included amongst factors that can influence the incident timeline. However, work zones might have affected some of the recorded incidents because of many ongoing construction projects in the study area. Work zones can affect various elements of the traffic incident timeline. For instance, work zones might make hard for responders to access incidents that have occurred in their close proximity. Future research can look upon the impacts of work zones in the response and clearance of incidents.

Moreover, the study analyzed the impact of incident on the traffic condition using historical speed data but there is an opportunity to understand the impacts of a traffic incident using video data analysis. This will improve the accuracy in the evaluation of the traffic incident timeline, especially elements that occur at the incident scene.

References for Chapter 1: Introduction

Amer, A., Roberts, E., Mangar, U., Kraft, W. H., Wanat, J. T., Cusolito, P. C., … Zhao, X. (2015). *Traffic Incident Management: Gap Analysis Primer*.

Conklin, C. A., Bahler, S. J., Belmore, Katherine L, H., Mark, I., John, S., Genevieve M, C., … Curley, C. E. (2013). Transportation Management Center Data Capture for Performance and Mobility Measures Reference Manual, 194.

Owens, N., Armstrong, A., Sullivan, P., Mitchell, C., Newton, D., Brewster, R., & Trego, T. (2010). Traffic Incident Management Handbook, (FHWA-HOP-10-013), 1–116. https://doi.org/10.1093/her/cys022

Palm Beach Post. (2018). Series of wrecks on I-95. Retrieved May 2, 2018, from https://www.palmbeachpost.com/news/breaking-news/breaking-pbso-deputy-shot-person-lantana-lanes-closed/d2K8F5BxGK0yC1wwBbjbzM/

References for Chapter 2: Paper 1

Amer, A., Roberts, E., Mangar, U., Kraft, W. H., Wanat, J. T., Cusolito, P. C., … Zhao, X. (2015). *Traffic Incident Management: Gap Analysis Primer*.

Brame, R., Paternoster, R., Mazerolle, P., & Piquero, A. (1998). Testing for the Equality of Maximum-Likelihood Regression Coefficients Between Two Independent Equations. *Journal of Quantitative Criminology*, *14*(3), 245–261. https://doi.org/10.1023/A:1023030312801

Carson, J., Mannering, F. L., Legg, B., Nee, J., & Nam, D. (1999). Are Programs Effective ? Findings from Washington State. *Transportation Research Record*, (1683). https://doi.org/doi.org/10.3141/1683-02

Chimba, D., Kutela, B., Ogletree, G., Horne, F., & Tugwell, M. (2014). Impact of Abandoned and Disabled Vehicles on Freeway Incident Duration. *Journal of Transportation Engineering*, *140*(3).

Chung, Y. (2010). Development of an accident duration prediction model on the Korean Freeway Systems. *Accident Analysis and Prevention*, *42*(1), 282–289. https://doi.org/10.1016/j.aap.2009.08.005

Chung, Y., & Yoon, B. J. (2012). Analytical method to estimate accident duration using archived speed profile and its statistical analysis. *KSCE Journal of Civil Engineering*, *16*(6), 1064–1070. https://doi.org/10.1007/s12205-012-1632-3

Conklin, C. A., Bahler, S. J., Belmore, Katherine L, H., Mark, I., John, S., Genevieve M, C., … Curley, C. E. (2013). Transportation Management Center Data Capture for Performance and Mobility Measures Reference Manual, 194.

FDOT. (2014). *State of Florida: Open Roads Policy Agreement*. Retrieved from http://www.fdot.gov/traffic/traf_incident/pdf/Open_Roads_Policy_FDOT_FHP.pdf

Garib, A., Radwan, A. E., & Al-Deek, H. (1997). Estimating Magnitude and Duration of Incident Delays. *Journal of Transportation Engineering*, *123*(DECEMBER), 459–466. https://doi.org/10.1061/(ASCE)0733-947X(1997)123:6(459)

Ghosh, I. (2012). Examination of the Factors Influencing the Clearance Time of Freeway Incidents. *Journal of Transportation Systems Engineering and Information Technology*, *12*(3), 75–89. https://doi.org/10.1016/S1570-6672(11)60204-3

Ghosh, I., & Savolainen, P. T. (2012). Analysis of Factors Affecting the Clearance 1 Time of Freeway Incidents. In *TRB 2012 Annual meeting*.

Golob, T. F., Recker, W. W., & Leonard, J. D. (1987). An analysis of the severity and incident duration of truck-involved freeway accidents. *Accident Analysis and Prevention*, *19*(5), 375–395. https://doi.org/10.1016/0001-4575(87)90023-6

Hojati, A. T., Ferreira, L., Washington, S., Charles, P., & Shobeirinejad, A. (2014). Modelling total duration of traffic incidents including incident detection and recovery time. *Accident Analysis and Prevention*, *71*, 296–305. https://doi.org/10.1016/j.aap.2014.06.006

Junhua, W., Haozhe, C., & Shi, Q. (2013). Estimating freeway incident duration using accelerated failure time modeling. *Safety Science*, *54*, 43–50. https://doi.org/10.1016/j.ssci.2012.11.009

Kaabi, A. (2013). *Modelling Traffic Accidents Using Duration Analysis Techniques : A Case Study of Abu Dhabi School of Civil Engineering and Geosciences By Abdulla Mohammed Saeed Al Kaabi A thesis submitted for the degree of Doctor of Philosophy in Transport at the Univers*.

Kaabi, A., Dissanayake, D., & Bird, R. (2012). Response Time of Highway Traffic Accidents in Abu Dhabi. *Transportation Research Record: Journal of the Transportation Research Board*, *2278*(2278), 95–103. https://doi.org/10.3141/2278-11

Karlaftis, M. G., Latoski, S. P., Richards, N. J., & Sinha, K. C. (1999). ITS Impacts on Safety and Traffic Management: An Investigation of Secondary Crash Causes. *ITS Journal*, *5*(1), 39–52. https://doi.org/10.1080/10248079908903756

Khattak, A. J., Schofer, J. L., & Wang, M.-H. (1995). A Simple Time Sequential Procedure for Predicting Freeway Incident Duration. *I V H S Journal*, *2*(2), 113–138. https://doi.org/10.1080/10248079508903820

Khattak, A., Wang, X., & Zhang, H. (2012). Incident management integration tool: dynamically predicting incident durations, secondary incident occurrence and incident delays. *IET Intelligent Transport Systems*, *6*(2), 204. https://doi.org/10.1049/iet-its.2011.0013

Kleinbaum, D. A., & Klein, M. (2005). *Survival Analysis: A Self_Learning Text*. *Journal of Chemical Information and Modeling* (Second). Springer Science+Business Media, Inc.

Lee, J., & Fazio, J. (2005). Influential Factors in Freeway Crash Response and Clearance Times by Emergency Management Services in Peak Periods. *Traffic Injury Prevention*, *6*(4), 331–339. https://doi.org/10.1080/15389580500255773

Li, R., & Shang, P. (2014). Incident duration modeling using flexible parametric hazard-based models. *Computational Intelligence and Neuroscience*, *2014*(1), 7–9. https://doi.org/10.1155/2014/723427

Li, X. (2017). Large-Scale Traffic Incident Duration Analysis : The Role of Multi-Agency Response and On-Scene Times. In *96th Annual Meeting for the Transportation Research Board*.

Liu, J., Zhang, R., Zhao, W., & Lv, Y. (2015). Variable selection in semiparametric hazard regression for multivariate survival data. *Journal of Multivariate Analysis*, *142*, 26–40. https://doi.org/10.1016/j.jmva.2015.07.015

Margiotta, R., Dowling, R., & Paracha, J. (2012). *Analysis, Modeling, and Simulation for Traffic Incident Management Applications*.

Nam, D., & Mannering, F. (2000). An exploratory hazard-based analysis of highway incident duration. *Transportation Research Part A: Policy and Practice*, *34*(2), 85–102. https://doi.org/10.1016/S0965-8564(98)00065-2

Owens, N., Armstrong, A., Sullivan, P., Mitchell, C., Newton, D., Brewster, R., & Trego, T. (2010). Traffic Incident Management Handbook, (FHWA-HOP-10-013), 1–116. https://doi.org/10.1093/her/cys022

Park, H., Haghani, A., & Zhang, X. (2016). Interpretation of Bayesian neural networks for predicting the duration of detected incidents. *Journal of Intelligent Transportation Systems*, *20*(4), 385–400. https://doi.org/10.1080/15472450.2015.1082428

Paternoster, R., Brame, R., Mazerolle, P., & Piquero, A. (1998). *Using the Correct Statistical Test for Equality of Regression Coefficients*. *Criminology* (Vol. 36). https://doi.org/10.1111/j.1745-9125.1998.tb01268.x

PB Farradyne. (2006). *Florida Traffic Incident Management Program: Strategic Plan*.

Pearce, V., & Subramaniam, S. (1998). *Incident Management: Detection, Verification, and Traffic Management*. *Intelligent Transportation Systems Field Operational Test Cross-Cutting Study*.

Schrank., D., Eisele., B., Lomax., T., & Bak., J. (2015). 2015 Urban Mobility Scorecard. *Texas A&M Transportation Institue*, *39*(August), 5. https://doi.org/DTRT06-G-0044

Smith, K., & Smith, B. L. (2001). *Forecasting the Clearance Time of Freeway Accidents*. Charlottesville,VA.

Spohn, C., & Homey, J. (1993). Rape law reform and the effect of victim characteristics on case processing. *Journal of Quantitative Criminology*, *9*(4), 383–409. https://doi.org/10.1007/BF01064110

Transportation Reseach Board. (2010). *Highway Capacity Manual*. *Hcm 2010*. Washington, D.C.

U.S.DOT Federal Highway Administration. (2017). FHWA Operations - Operations Story. Retrieved July 17, 2017, from http://www.ops.fhwa.dot.gov/aboutus/opstory.htm

USDOT-ITS. (2000). *Incident Management Successful Practices: A Cross-Cutting Study*.

USF. (2005). *Best Practices for Traffic Incident Management in Florida*.

Wang, W., Chen, H., & Bell, M. C. (2005). Vehicle Breakdown Duration Modeling. *Journal of*

Transportation and Statistics, *8*(1), 75–84.

Washington, S., Karlaftis, M. G., & Mannering, F. L. (2003). Statistical and econometric techniques for transportation data analysis. *CRC/Chapman & Hall Press, New York, NY*.

Zeng, X., & Songchitruksa, P. (2010). Empirical Method for Estimating Traffic Incident Recovery Time. *Transportation Research Record: Journal of the Transportation Research Board*, *2178*(2178), 119–127. https://doi.org/10.3141/2178-13

Zhang, H., & Khattak, A. J. (2010). Analysis of Cascading Incident Event Durations on Urban Freeways. *Transportation Research Record: Journal of the Transportation Research Board*, *2178*(2178), 30–39. https://doi.org/10.3141/2178-04

Zhang, H., Zhang, Y., & Khattak, A. (2012). Analysis of Large-Scale Incidents on Urban Freeways. *Transportation Research Record: Journal of the Transportation Research Board*, *2278*, 74–84. https://doi.org/10.3141/2278-09

Zhou, H., & Tian, Z. (2012). Modeling Analysis of Incident and Roadway Clearance Time. *Procedia - Social and Behavioral Sciences*, *43*, 349–355. https://doi.org/10.1016/j.sbspro.2012.04.108

References for Chapter 3: Paper 2

Amer, A., Roberts, E., Mangar, U., Kraft, W. H., Wanat, J. T., Cusolito, P. C., … Zhao, X. (2015). *Traffic Incident Management: Gap Analysis Primer*.

Carson, J., Mannering, F. L., Legg, B., Nee, J., & Nam, D. (1999). Are Programs Effective ? Findings from Washington State. *Transportation Research Record*, (1683). https://doi.org/doi.org/10.3141/1683-02

Chimba, D., Kutela, B., Ogletree, G., Horne, F., & Tugwell, M. (2014). Impact of Abandoned and Disabled Vehicles on Freeway Incident Duration. *Journal of Transportation Engineering*, *140*(3).

Chung, Y. (2010). Development of an accident duration prediction model on the Korean Freeway Systems. *Accident Analysis and Prevention*, *42*(1), 282–289. https://doi.org/10.1016/j.aap.2009.08.005

Chung, Y., & Yoon, B. J. (2012). Analytical method to estimate accident duration using archived speed profile and its statistical analysis. *KSCE Journal of Civil Engineering*, *16*(6), 1064–1070. https://doi.org/10.1007/s12205-012-1632-3

Conklin, C. A., Bahler, S. J., Belmore, Katherine L, H., Mark, I., John, S., Genevieve M, C., … Curley, C. E. (2013). Transportation Management Center Data Capture for Performance and Mobility Measures Reference Manual, 194.

FDOT. (2014). *State of Florida: Open Roads Policy Agreement*. Retrieved from http://www.fdot.gov/traffic/traf_incident/pdf/Open_Roads_Policy_FDOT_FHP.pdf

Garib, A., Radwan, A. E., & Al-Deek, H. (1997). Estimating Magnitude and Duration of Incident Delays. *Journal of Transportation Engineering*, *123*(DECEMBER), 459–466. https://doi.org/10.1061/(ASCE)0733-947X(1997)123:6(459)

Ghosh, I. (2012). Examination of the Factors Influencing the Clearance Time of Freeway Incidents. *Journal of Transportation Systems Engineering and Information Technology*, *12*(3), 75–89. https://doi.org/10.1016/S1570-6672(11)60204-3

Ghosh, I., & Savolainen, P. T. (2012). Analysis of Factors Affecting the Clearance 1 Time of Freeway Incidents. In *TRB 2012 Annual meeting*.

Golob, T. F., Recker, W. W., & Leonard, J. D. (1987). An analysis of the severity and incident duration of truck-involved freeway accidents. *Accident Analysis and Prevention*, *19*(5), 375–395. https://doi.org/10.1016/0001-4575(87)90023-6

Hojati, A. T., Ferreira, L., Washington, S., Charles, P., & Shobeirinejad, A. (2014). Modelling total duration of traffic incidents including incident detection and recovery time. *Accident Analysis and Prevention*, *71*, 296–305. https://doi.org/10.1016/j.aap.2014.06.006

Jeihani, M., James, P., Saka, A. A., & Ardeshiri, A. (2015). Traffic recovery time estimation under different flow regimes in traffic simulation. *Journal of Traffic and Transportation Engineering (English Edition)*, *2*(5), 291–300. https://doi.org/10.1016/j.jtte.2015.08.001

Junhua, W., Haozhe, C., & Shi, Q. (2013). Estimating freeway incident duration using accelerated failure time modeling. *Safety Science*, *54*, 43–50. https://doi.org/10.1016/j.ssci.2012.11.009

Kaabi, A. (2013). *Modelling Traffic Accidents Using Duration Analysis Techniques : A Case Study of Abu Dhabi School of Civil Engineering and Geosciences By Abdulla Mohammed Saeed Al Kaabi A thesis submitted for the degree of Doctor of Philosophy in Transport at the Univers*.

Kaabi, A., Dissanayake, D., & Bird, R. (2012). Response Time of Highway Traffic Accidents in Abu Dhabi. *Transportation Research Record: Journal of the Transportation Research Board*, *2278*(2278), 95–103. https://doi.org/10.3141/2278-11

Karlaftis, M. G., Latoski, S. P., Richards, N. J., & Sinha, K. C. (1999). ITS Impacts on Safety and Traffic Management: An Investigation of Secondary Crash Causes. *ITS Journal*, *5*(1), 39–52. https://doi.org/10.1080/10248079908903756

Khattak, A. J., Schofer, J. L., & Wang, M.-H. (1995). A Simple Time Sequential Procedure for Predicting Freeway Incident Duration. *I V H S Journal*, *2*(2), 113–138. https://doi.org/10.1080/10248079508903820

Khattak, A., Wang, X., & Zhang, H. (2012). Incident management integration tool: dynamically predicting incident durations, secondary incident occurrence and incident delays. *IET Intelligent Transport Systems*, *6*(2), 204. https://doi.org/10.1049/iet-its.2011.0013

Kleinbaum, D. A., & Klein, M. (2005). *Survival Analysis: A Self_Learning Text*. *Journal of Chemical Information and Modeling* (Second). Springer Science+Business Media, Inc.

Lee, J., & Fazio, J. (2005). Influential Factors in Freeway Crash Response and Clearance Times by Emergency Management Services in Peak Periods. *Traffic Injury Prevention*, *6*(4), 331–339. https://doi.org/10.1080/15389580500255773

Li, R., & Shang, P. (2014). Incident duration modeling using flexible parametric hazard-based models. *Computational Intelligence and Neuroscience*, *2014*(1), 7–9. https://doi.org/10.1155/2014/723427

Li, X. (2017). Large-Scale Traffic Incident Duration Analysis : The Role of Multi-Agency Response and On-Scene Times. In *96th Annual Meeting for the Transportation Research Board*.

Margiotta, R., Dowling, R., & Paracha, J. (2012). *Analysis, Modeling, and Simulation for Traffic Incident Management Applications*.

Nam, D., & Mannering, F. (2000). An exploratory hazard-based analysis of highway incident duration. *Transportation Research Part A: Policy and Practice*, *34*(2), 85–102.

https://doi.org/10.1016/S0965-8564(98)00065-2

Owens, N., Armstrong, A., Sullivan, P., Mitchell, C., Newton, D., Brewster, R., & Trego, T. (2010). Traffic Incident Management Handbook, (FHWA-HOP-10-013), 1–116. https://doi.org/10.1093/her/cys022

Park, H., Haghani, A., & Zhang, X. (2016). Interpretation of Bayesian neural networks for predicting the duration of detected incidents. *Journal of Intelligent Transportation Systems*, *20*(4), 385–400. https://doi.org/10.1080/15472450.2015.1082428

PB Farradyne. (2006). *Florida Traffic Incident Management Program: Strategic Plan*.

Pearce, V., & Subramaniam, S. (1998). *Incident Management: Detection, Verification, and Traffic Management. Intelligent Transportation Systems Field Operational Test Cross-Cutting Study*.

Schrank., D., Eisele., B., Lomax., T., & Bak., J. (2015). 2015 Urban Mobility Scorecard. *Texas A&M Transportation Institue*, *39*(August), 5. https://doi.org/DTRT06-G-0044

Smith, K., & Smith, B. L. (2001). *Forecasting the Clearance Time of Freeway Accidents*. Charlottesville,VA.

Transportation Reseach Board. (2010). *Highway Capacity Manual*. *Hcm 2010*. Washington, D.C.

U.S.DOT Federal Highway Administration. (2017). FHWA Operations - Operations Story. Retrieved July 17, 2017, from http://www.ops.fhwa.dot.gov/aboutus/opstory.htm

USDOT-ITS. (2000). *Incident Management Successful Practices: A Cross-Cutting Study*.

USF. (2005). *Best Practices for Traffic Incident Management in Florida*.

Wang, W., Chen, H., & Bell, M. C. (2005). Vehicle Breakdown Duration Modeling. *Journal of Transportation and Statistics*, *8*(1), 75–84.

Washington, S., Karlaftis, M. G., & Mannering, F. L. (2003). Statistical and econometric techniques for transportation data analysis. *CRC/Chapman & Hall Press, New York, NY*.

Zeng, X., & Songchitruksa, P. (2010). Empirical Method for Estimating Traffic Incident Recovery Time. *Transportation Research Record: Journal of the Transportation Research Board*, *2178*(2178), 119–127. https://doi.org/10.3141/2178-13

Zhang, H., & Khattak, A. J. (2010). Analysis of Cascading Incident Event Durations on Urban Freeways. *Transportation Research Record: Journal of the Transportation Research Board*, *2178*(2178), 30–39. https://doi.org/10.3141/2178-04

Zhang, H., Zhang, Y., & Khattak, A. (2012). Analysis of Large-Scale Incidents on Urban Freeways. *Transportation Research Record: Journal of the Transportation Research Board*, *2278*, 74–84. https://doi.org/10.3141/2278-09

Zhou, H., & Tian, Z. (2012). Modeling Analysis of Incident and Roadway Clearance Time. *Procedia - Social and Behavioral Sciences*, *43*, 349–355. https://doi.org/10.1016/j.sbspro.2012.04.108

References for Chapter 4: Paper 3

Amer, A., Roberts, E., Mangar, U., Kraft, W. H., Wanat, J. T., Cusolito, P. C., … Zhao, X. (2015). *Traffic Incident Management: Gap Analysis Primer*.

Carson, J., Mannering, F. L., Legg, B., Nee, J., & Nam, D. (1999). Are Programs Effective ? Findings from Washington State. *Transportation Research Record*, (1683).

https://doi.org/doi.org/10.3141/1683-02

Chimba, D., Kutela, B., Ogletree, G., Horne, F., & Tugwell, M. (2014). Impact of Abandoned and Disabled Vehicles on Freeway Incident Duration. *Journal of Transportation Engineering*, *140*(3).

Chung, Y. (2010). Development of an accident duration prediction model on the Korean Freeway Systems. *Accident Analysis and Prevention*, *42*(1), 282–289. https://doi.org/10.1016/j.aap.2009.08.005

Chung, Y., & Yoon, B. J. (2012). Analytical method to estimate accident duration using archived speed profile and its statistical analysis. *KSCE Journal of Civil Engineering*, *16*(6), 1064–1070. https://doi.org/10.1007/s12205-012-1632-3

Conklin, C. A., Bahler, S. J., Belmore, Katherine L, H., Mark, I., John, S., Genevieve M, C., … Curley, C. E. (2013). Transportation Management Center Data Capture for Performance and Mobility Measures Reference Manual, 194.

FDOT. (2014). *State of Florida: Open Roads Policy Agreement*. Retrieved from http://www.fdot.gov/traffic/traf_incident/pdf/Open_Roads_Policy_FDOT_FHP.pdf

Garib, A., Radwan, A. E., & Al-Deek, H. (1997). Estimating Magnitude and Duration of Incident Delays. *Journal of Transportation Engineering*, *123*(DECEMBER), 459–466. https://doi.org/10.1061/(ASCE)0733-947X(1997)123:6(459)

Ghosh, I. (2012). Examination of the Factors Influencing the Clearance Time of Freeway Incidents. *Journal of Transportation Systems Engineering and Information Technology*, *12*(3), 75–89. https://doi.org/10.1016/S1570-6672(11)60204-3

Ghosh, I., & Savolainen, P. T. (2012). Analysis of Factors Affecting the Clearance 1 Time of Freeway Incidents. In *TRB 2012 Annual meeting*.

Golob, T. F., Recker, W. W., & Leonard, J. D. (1987). An analysis of the severity and incident duration of truck-involved freeway accidents. *Accident Analysis and Prevention*, *19*(5), 375–395. https://doi.org/10.1016/0001-4575(87)90023-6

Hojati, A. T., Ferreira, L., Washington, S., Charles, P., & Shobeirinejad, A. (2014). Modelling total duration of traffic incidents including incident detection and recovery time. *Accident Analysis and Prevention*, *71*, 296–305. https://doi.org/10.1016/j.aap.2014.06.006

Honda, T., & Karl Härdle, W. (2014). Variable selection in Cox regression models with varying coefficients. *Journal of Statistical Planning and Inference*, *148*, 67–81. https://doi.org/10.1016/j.jspi.2013.12.002

Junhua, W., Haozhe, C., & Shi, Q. (2013). Estimating freeway incident duration using accelerated failure time modeling. *Safety Science*, *54*, 43–50. https://doi.org/10.1016/j.ssci.2012.11.009

Kaabi, A. (2013). *Modelling Traffic Accidents Using Duration Analysis Techniques : A Case Study of Abu Dhabi School of Civil Engineering and Geosciences By Abdulla Mohammed Saeed Al Kaabi A thesis submitted for the degree of Doctor of Philosophy in Transport at the University of Newcastle*.

Kaabi, A., Dissanayake, D., & Bird, R. (2012). Response Time of Highway Traffic Accidents in Abu Dhabi. *Transportation Research Record: Journal of the Transportation Research Board*, *2278*(2278), 95–103. https://doi.org/10.3141/2278-11

Karlaftis, M. G., Latoski, S. P., Richards, N. J., & Sinha, K. C. (1999). ITS Impacts on Safety and Traffic Management: An Investigation of Secondary Crash Causes. *ITS Journal*, *5*(1), 39–52. https://doi.org/10.1080/10248079908903756

Khattak, A. J., Schofer, J. L., & Wang, M.-H. (1995). A Simple Time Sequential Procedure for Predicting Freeway Incident Duration. *I V H S Journal*, *2*(2), 113–138. https://doi.org/10.1080/10248079508903820

Khattak, A., Wang, X., & Zhang, H. (2012). Incident management integration tool: dynamically predicting incident durations, secondary incident occurrence and incident delays. *IET Intelligent Transport Systems*, *6*(2), 204. https://doi.org/10.1049/iet-its.2011.0013

Kleinbaum, D. A., & Klein, M. (2005). *Survival Analysis: A Self_Learning Text*. *Journal of Chemical Information and Modeling* (Second). Springer Science+Business Media, Inc.

Lee, J., & Fazio, J. (2005). Influential Factors in Freeway Crash Response and Clearance Times by Emergency Management Services in Peak Periods. *Traffic Injury Prevention*, *6*(4), 331–339. https://doi.org/10.1080/15389580500255773

Li, R., & Shang, P. (2014). Incident duration modeling using flexible parametric hazard-based models. *Computational Intelligence and Neuroscience*, *2014*(1), 7–9. https://doi.org/10.1155/2014/723427

Li, X. (2017). Large-Scale Traffic Incident Duration Analysis : The Role of Multi-Agency Response and On-Scene Times. In *96th Annual Meeting for the Transportation Research Board*.

Liu, J., Zhang, R., Zhao, W., & Lv, Y. (2015). Variable selection in semiparametric hazard regression for multivariate survival data. *Journal of Multivariate Analysis*, *142*, 26–40. https://doi.org/10.1016/j.jmva.2015.07.015

Margiotta, R., Dowling, R., & Paracha, J. (2012). *Analysis, Modeling, and Simulation for Traffic Incident Management Applications*.

Nam, D., & Mannering, F. (2000). An exploratory hazard-based analysis of highway incident duration. *Transportation Research Part A: Policy and Practice*, *34*(2), 85–102. https://doi.org/10.1016/S0965-8564(98)00065-2

Owens, N., Armstrong, A., Sullivan, P., Mitchell, C., Newton, D., Brewster, R., & Trego, T. (2010). Traffic Incident Management Handbook, (FHWA-HOP-10-013), 1–116. https://doi.org/10.1093/her/cys022

Palm Beach Post. (2018). Series of wrecks on I-95. Retrieved May 2, 2018, from https://www.palmbeachpost.com/news/breaking-news/breaking-pbso-deputy-shot-person-lantana-lanes-closed/d2K8F5BxGK0yC1wwBbjbzM/

Park, H., Haghani, A., & Zhang, X. (2016). Interpretation of Bayesian neural networks for predicting the duration of detected incidents. *Journal of Intelligent Transportation Systems*, *20*(4), 385–400. https://doi.org/10.1080/15472450.2015.1082428

PB Farradyne. (2006). *Florida Traffic Incident Management Program: Strategic Plan*.

Pearce, V., & Subramaniam, S. (1998). *Incident Management: Detection, Verification, and Traffic Management*. *Intelligent Transportation Systems Field Operational Test Cross-Cutting Study*.

Schrank., D., Eisele., B., Lomax., T., & Bak., J. (2015). 2015 Urban Mobility Scorecard. *Texas*

A&M Transportation Institue, *39*(August), 5. https://doi.org/DTRT06-G-0044

Smith, K., & Smith, B. L. (2001). *Forecasting the Clearance Time of Freeway Accidents*. Charlottesville,VA.

Spohn, C., & Homey, J. (1993). Rape law reform and the effect of victim characteristics on case processing. *Journal of Quantitative Criminology*, *9*(4), 383–409. https://doi.org/10.1007/BF01064110

Tibshirani, R. (1996). Regression Selection and Shrinkage via the Lasso. *Journal of the Royal Statistical Society B*. https://doi.org/10.2307/2346178

Transportation Reseach Board. (2010). *Highway Capacity Manual*. *Hcm 2010*. Washington, D.C.

U.S.DOT Federal Highway Administration. (2017). FHWA Operations - Operations Story. Retrieved July 17, 2017, from http://www.ops.fhwa.dot.gov/aboutus/opstory.htm

USDOT-ITS. (2000). *Incident Management Successful Practices: A Cross-Cutting Study*.

USF. (2005). *Best Practices for Traffic Incident Management in Florida*.

Wang, W., Chen, H., & Bell, M. C. (2005). Vehicle Breakdown Duration Modeling. *Journal of Transportation and Statistics*, *8*(1), 75–84.

Washington, S., Karlaftis, M. G., & Mannering, F. L. (2003). Statistical and econometric techniques for transportation data analysis. *CRC/Chapman & Hall Press, New York, NY*.

Zeng, X., & Songchitruksa, P. (2010). Empirical Method for Estimating Traffic Incident Recovery Time. *Transportation Research Record: Journal of the Transportation Research Board*, *2178*(2178), 119–127. https://doi.org/10.3141/2178-13

Zhang, H., & Khattak, A. J. (2010). Analysis of Cascading Incident Event Durations on Urban Freeways. *Transportation Research Record: Journal of the Transportation Research Board*, *2178*(2178), 30–39. https://doi.org/10.3141/2178-04

Zhang, H., Zhang, Y., & Khattak, A. (2012). Analysis of Large-Scale Incidents on Urban Freeways. *Transportation Research Record: Journal of the Transportation Research Board*, *2278*, 74–84. https://doi.org/10.3141/2278-09

Zhou, H., & Tian, Z. (2012). Modeling Analysis of Incident and Roadway Clearance Time. *Procedia - Social and Behavioral Sciences*, *43*, 349–355. https://doi.org/10.1016/j.sbspro.2012.04.108

Zou, H. (2008). A note on path-based variable selection in the penalized proportional hazards model. *Biometrika*, *95*(1), 241–247. https://doi.org/10.1093/biomet/asm083

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Masters of Science in Civil Engineering, August 2016-Present

University of Dar – es – Salaam, Tanzania

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Relative Work Experience

University of North Florida, Jacksonville, Florida. August 2016-Present

Graduate Research Assistant (Transportation safety modeling, Traffic operations)

1. Collecting, processing, interpreting, analyzing, and compiling traffic data obtained for research projects.
2. Worked on a FDOT sponsored project "Evaluation of Incident Response Improvements for Statewide Application: Learning from the New Regional Traffic Management Center in Jacksonville, Florida".

Graduate Teaching/Tutorial Assistant

1. Preparing and carrying out lab tutorials for Microstation (SS4) with Geopak, Fall, 2017 and Spring, 2018. Lab involved creating roadway centerline, corridor modelling, superelevation, template design, roadway and profile sheets and cutting sheets.
2. Tutorial Assistant for Construction materials class, Fall 2017

Publications

Peer-reviewed papers conference proceedings

1. Evaluating the Impact and Clearance Duration of Freeway Incidents. Proceedings of the Transportation Research Board's 97th Annual Meeting, Paper No. 18-06040, Washington DC, USA, January 7-11, 2018.

2. Influence of Intersection Characteristics on Elderly Drivers Crash Involvement. Proceedings of the Transportation Research Board's 97th Annual Meeting, Paper No. 18-06625, Washington DC, USA, January 7-11, 2018.

Papers considered for journal publication

1. Investigating Proximity of Crash Locations to Aging Pedestrian Residences
2. Evaluating the Impact of Incident Timeline Elements on Clearance Duration
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Campus Involvement and Volunteer Experience

1. Member of the Institute of Engineers Tanzania (IET).
2. American Society of Highway Engineers, UNF chapter.
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